ABSTRACT

CHO, MOON HEE. Essays on the Effect of GATT/WTO and Financial Crisis on International Trade. (Under the direction of Xiaoyong Zheng and Ivan T. Kandilov.)

The whole thesis consists of three chapters.

In chapter 1, I develop a Bayesian estimation method for inferring a dynamic panel data gravity model. My method deals with the many zeros problem and at the same time allows for lagged dependent variables and multiple sets of unobserved effects. I apply the Bayesian estimation algorithm to re-examine the effect of GATT/WTO membership on trade. I find that my dynamic gravity model fits the data better than the static version of the same model, and trade flow in the previous period has a large and positive effect on trade flow in the current period. I also find that GATT/WTO membership does not appear to have an effect on trade flow. This result is consistent with the findings by Rose (2004), but not with those of Liu (2009), who uses the same dataset. This shows the importance of including lagged dependent variables and multiple sets of unobserved effects in gravity model estimation.

In chapter 2, I develop a method to estimate a dynamic gravity model with multiple sets of unobserved effects, with only the conditional mean assumption for the dependent variable. My method deals with the many zeros problem and allows for lagged dependent variables and time-varying exporter and importer fixed effects as well as time-invariant country-pair fixed effects. I find that trade flow in the previous period still has a large and positive effect on trade flow in the current period after controlling for multiple sets of unobserved effects.

In chapter 3, I investigate the impact of a banking crisis on international trade in services. Many studies have tried to explain how a banking crisis affects international trade flows. However, despite the growing importance of services trade, the existing literature has focused on the impact of banking crises on goods trade. This is because, until recently, no internationally comparable bilateral services trade data were available to measure the effects of such crises. The OECD now provides bilateral services trade data, and it is thus possible to examine the effect of the recent global crisis on services trade. Because there is heterogeneity within services, I hypothesize that the exporter's and importer's banking crises affect each services sector's trade differently. I find that both the exporter's and the importer's banking crises have a negative effect on goods-related services trade, such as other commercial services trade and transportation services trade. However, there is no significant effect of banking crises on travel services trade.

Essays on the Effect of GATT/WTO and Financial Crisis on International Trade

by
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DEDICATION

To my parents.

BIOGRAPHY

Moon Hee Cho was born in Cheongju, South Korea. He received his bachelor's degree in Business Administration with a minor in Economics from Yonsei University. He received his master's degree in Economics from North Carolina State University. He started his Ph.D. degree in Economics at North Carolina State University in 2009.

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Chapter 1

Bayesian Estimation of Dynamic Panel Data Gravity Model

1.1 Introduction

Since the seminal work by Tinbergen (1962), the gravity model has been widely used in the empirical trade literature to examine various determinants of trade flow among different countries.[1] Analogous to Newton's law of universal gravitation, the gravity model states that the trade flow from one country to another depends proportionally on the product of the two countries' GDPs and is inversely proportional to various trade barriers. Typically, datasets used to estimate the gravity model are aggregate at the national, industry or product level and are panel, collected from many country pairs and across many years.

In most of the empirical work (e.g., Frankel and Wei 1993; Harrigan 1993; Eichengreen and Irwin 1995; McCallum 1995; Frankel, Stein and Wei 1997; Rose 2000; Alesina, Barro and Tenreyro 2002; Frankel and Rose 2002; Anderson and van Wincoop 2003), a static panel data model is used as the main specification. In such a model, trade volumes in previous periods, or the lagged dependent variables, are not included as control variables. This is inconsistent with the recent evidence from micro- or firm-level studies of determinants of trade patterns. Roberts and Tybout (1997) and Bernard and Jensen (2004) both find that sunk entry and exit costs play an important role in firms' export behavior and firms that exported in previous periods are more likely to export in the current period. Clerides, Lach and Tybout (1998) find evidence of positive regional externalities on export, that is, the presence of other exporters in the same region make producers more likely to enter foreign markets. De Loecker (2013) finds substantial productivity gains from exporting, which makes exporting firms more competitive.

[1] See, for example, Anderson (1979) and Anderson and van Wincoop (2003) for a theoretical foundation of the gravity model.

These studies imply that trade flow in previous periods is an important determinant of trade flow in the current period at the micro level. If this is true, then the same pattern should be observed at the aggregate level as well, because aggregate data are simply the summation of micro-level data. Furthermore, recently Olivero and Yotov (2012) have extended the theoretical foundations of the gravity model by Anderson (1979) and Anderson and van Wincoop (2003) from static to dynamic. One of the key implications from their theoretical model for empirical analysis is that lagged trade volumes should be included as control variables in gravity model estimation. Otherwise, the estimation may yield biased estimates because of the omitted variable problem.

In addition, as panel data have a time dimension, serial correlation in the error term is a potential concern. Not controlling for serial correlation in the estimation can lead to biased estimates of the standard errors and hence invalid statistical inference. This is particularly relevant in the gravity model estimation context as researchers often rely on the t statistics of the coefficient estimates to judge the importance of specific economic variables as determinants of trade flow. Controlling for the lagged dependent variable in the estimation makes the serially uncorrelated error assumption more likely to hold. Indeed, Wooldridge (2013, Chapter 12) demonstrates that a model with an autoregressive error term can always be re-written as a model with lagged dependent variables and a serially uncorrelated error term.

In this chapter, I extend the work by Ranjan and Tobias (2007) to estimate a dynamic version of the threshold Tobit model in the framework of Eaton and Tamura (1994) with multiple sets of unobserved effects. The threshold Tobit model offers an empirical strategy to deal with the fact that there are many zero observations in a typical trade dataset, especially at the industry or product level.[2] Studies in the literature such as Rose (2004) have estimated dynamic specifications of the gravity model. However, most studies simply drop the country pairs with zero trade volume and/or do not control for multiple sets of unobserved effects. The main contribution of my study is that I propose a Bayesian estimation algorithm that deals with the many zeros problem and at the same time allows for lagged dependent variables and multiple sets of unobserved effects. This turns out to be a challenging task. The resulting model is a dynamic nonlinear panel data model. In such models, a well known problem is the initial conditions problem discussed by Arellano and Honore (2001) and Hsiao (2003). I address this problem using the empirical strategy recently proposed by Wooldridge (2005).

I then apply my Bayesian estimation algorithm to re-examine the effect of GATT/WTO membership on trade. I find that my dynamic gravity model fits the data better than the static version of the same model and trade flow in the previous period has a large and positive effect on trade flow in the current period. I also find that GATT/WTO membership does not have a

[2]Another strategy to deal with the many zeros problem is the Poisson pseudo maximum likelihood (PPML) method proposed by Santos Silva and Tenreyro (2006).

positive effect on trade flow. This result is consistent with the findings of Rose (2004), but not with the belief that GATT/WTO promotes trade and with findings from several other recent studies.

The rest of this chapter is organized as follows. My empirical model is introduced in the next section. Section 3 proposes the Bayesian estimation algorithm, which is applied in Section 4 to re-examine the effect of GATT/WTO membership on trade. The final section concludes. Technical details are relegated to the appendices.

1.2 The Empirical Model

Following Eaton and Tamura (1994) and Ranjan and Tobias (2007), I estimate the following dynamic threshold Tobit model

$$\log(Y^*_{ijt} + \tau) = \log(Y_{ijt-1} + \tau)\rho + z_{ijt}\theta + c_{ij} + d_{it} + e_{jt} + \varepsilon_{ijt}, \tag{1.1}$$

where

$$Y_{ijt} = \begin{cases} Y^*_{ijt} & \text{if } Y^*_{ijt} > 0 \text{ or } W^*_{ijt} = Y^*_{ijt} + \tau > \tau \\ 0 & \text{if } -\tau < Y^*_{ijt} \leq 0 \text{ or } 0 < W^*_{ijt} = Y^*_{ijt} + \tau \leq \tau \end{cases}.$$

In (1.1), W^*_{ijt} denotes the desired amount of trade between exporter i and importer j in year t. The threshold parameter τ can be interpreted as the amount of trade that is lost in transit. If the desired amount of trade is larger than the threshold, then the observed trade flow, Y_{ijt}, equals the desired amount minus the threshold. Otherwise, I observe Y_{ijt} equals 0.

I model the dynamics of the trade flow using the autoregressive of order one (AR(1)) specification.[3] z_{ijt} is a vector of observed exporter and importer characteristic variables that are likely to determine the trade flow. Variables often used in gravity model estimation include proxies of the country size such as GDP and population, geographic variables such as distance and whether the two countries share a common border or are in the same hemisphere, language barrier variables, and variables for country ties such as colonial relationship in the past and whether there is a regional trade agreement between two countries.

In addition to the observed variables, I also include three terms in the model to control for factors that are likely to influence the trade flow, but are not observed by econometricians. c_{ij} captures the time-invariant unobserved country pair heterogeneity. The exporter-year term d_{it} and importer-year term e_{jt} capture time varying country specific unobserved heterogeneity such

[3]Ideally, I would like to include the term $\log(Y^*_{ijt-1} + \tau)$ instead of $\log(Y_{ijt-1} + \tau)$ as one of the explanatory variables, resulting in an AR(1) model of the desired amount of trade. However, doing this will make the estimation very difficult, if not feasible, to implement. See Appendix B for the Bayesian estimation procedure and its associated computational problems for this specification. Since $\log(Y_{ijt-1} + \tau)$ is fairly close to $\log(Y^*_{ijt-1} + \tau)$, I believe that using $\log(Y_{ijt-1} + \tau)$ instead of $\log(Y^*_{ijt-1} + \tau)$ will have little impact on the main parameter of interest, that is, θ. Another possible specification is to use Y_{ijt-1} in place of $\log(Y_{ijt-1} + \tau)$.

as the multilateral resistance specified by Anderson and Van Wincoop (2003) and Ranjan and Tobias (2007). Finally, ε_{ijt} is assumed to be an idiosyncratic error term with i.i.d. $N\left(0,\sigma_{\varepsilon}^{2}\right)$. Another interpretation of the model is that $c_{ij}+d_{it}+e_{jt}+\varepsilon_{ijt}$ is a composite error term and $c_{ij}+d_{it}+e_{jt}$ is the part of the error term that captures the serial correlation over time, importers, and exporters. This, together with the inclusion of lagged dependent variable, makes the i.i.d. assumption of ε_{ijt} more likely to hold.

Following Ranjan and Tobias (2007) and Kandilov and Zheng (2011), I use the correlated random effects specification for the unobserved heterogeneity terms. As it is well known, for dynamic panel data models with unobserved effects, an important issue is the treatment of the initial observations. Wooldridge (2005) discusses the advantages and disadvantages of several approaches in the literature for addressing this issue for nonlinear panel data models. He also suggests a simple alternative approach that is to model the distribution of the unobserved pair specific effect conditional on the initial observations and exogenous variables. One of the advantages of Wooldridge's approach is that by specifying the (auxiliary) distribution of the unobserved pair specific heterogeneity conditional on the initial conditions to be normal, estimation is greatly simplified.[4]

In this chapter, I adopt this approach and model the relationship between the unobserved pair specific heterogeneity and the initial conditions, conditional on observed strictly exogenous variables as

$$c_{ij}=\delta_{c1}Y_{ij0}+\overline{z}_{ij}\delta_{c2}+\alpha_{ij}, \tag{1.2}$$

where $\alpha_{ij}|Y_{ij0},\overline{z}_{ij}\overset{iid}{\sim}N(0,\sigma_{\alpha}^{2})$. The initial value of the dependent variable is Y_{ij0}, and $\overline{z}_{ij}$ is the average of z_{ijt} over all time periods as in Chib and Jeliazkov (2006).[5] Similarly, the unobserved exporter-year specific heterogeneity, d_{it}, and the unobserved importer-year specific heterogeneity, e_{jt}, are specified as

$$\begin{aligned} d_{it}&=\overline{z}_{it}\delta_{d}+\zeta_{it},\ \zeta_{it}|\overline{z}_{it}\overset{iid}{\sim}N(0,\sigma_{\zeta}^{2}),\\ e_{jt}&=\overline{z}_{jt}\delta_{e}+\upsilon_{jt},\ \upsilon_{jt}|\overline{z}_{jt}\overset{iid}{\sim}N(0,\sigma_{\upsilon}^{2}), \end{aligned} \tag{1.3}$$

where $\overline{z}_{it}$ is the average of z_{ijt} over all importers of exporter i and $\overline{z}_{jt}$ is the average of z_{ijt} over all exporters of importer j.[6]

[4] Loudermilk (2007), Li and Zheng (2008) and Kandilov and Zheng (2011) apply the same idea as Wooldridge (2005) to a dynamic panel data model with fractional dependent variables, a dynamic panel data Tobit model and a dynamic panel data Probit model, respectively.

[5] For identification purposes, those time-constant variables cannot be in both z_{ijt} and $\overline{z}_{ij}$.

[6] Note the initial condition problem does not apply to d_{it} and e_{jt}, as Y_{ij0} does not depend on d_{it} and e_{jt} for $t\geq 1$. Also, again, for identification purposes, those importer-constant variables cannot be in both z_{ijt} and $\overline{z}_{it}$ and those exporter-constant variables cannot be in both z_{ijt} and $\overline{z}_{jt}$.

1.3 Bayesian Estimation

I fit the model using the Gibbs sampler, and to this end I derive the posterior conditionals of the model. Denote $V^*_{ijt} = \log\left(Y^*_{ijt} + \tau\right)$ and the posterior function for the parameters and latent variables $\left\{V^*_{ijt}\right\}^{t^1_{ij}}_{t=t^0_{ij},\forall ij}$, $\{c_{ij}\}_{\forall ij}$, $\{d_{it}\}^{t^1_i}_{t=t^0_i,\forall i}$, $\{e_{jt}\}^{t^1_j}_{t=t^0_j,\forall j}$ can be written as

$$
\begin{aligned}
&posterior\left(\begin{array}{c}\left\{V^*_{ijt}\right\}^{t^1_{ij}}_{t=t^0_{ij},\forall ij}, \{c_{ij}\}_{\forall ij}, \{d_{it}\}^{t^1_i}_{t=t^0_i,\forall i}, \{e_{jt}\}^{t^1_j}_{t=t^0_j,\forall j}, \tau, \beta, \delta, \sigma^2 \\ \left| \{Y_{ijt}\}^{t^1_{ij}}_{t=t^0_{ij},\forall ij}, \{z_{ijt}\}^{t^1_{ij}}_{t=t^0_{ij},\forall ij}\right.\end{array}\right) \\
&\propto prior\left(\tau, \beta, \delta, \sigma^2\right) \\
&*\prod_{i=1}^{I}\prod_{j=1}^{J_i}\prod_{t=t^0_{ij}}^{t^1_{ij}}\left\{\begin{array}{c}\left\{I\left[V^*_{ijt} > \log(\tau)\right] I\left[Y_{ijt} = \exp(V^*_{ijt}) - \tau\right] + I\left[V^*_{ijt} \leq \log(\tau)\right] I(Y_{ijt} = 0)\right\} \\ *\frac{1}{\sqrt{2\pi\sigma^2_\varepsilon}} \exp\left[-\frac{1}{2\sigma^2_\varepsilon}(V^*_{ijt} - w_{ijt}\beta - c_{ij} - d_{it} - e_{jt})^2\right]\end{array}\right\} \\
&*\prod_{i=1}^{I}\prod_{j=1}^{J_i}\left\{\frac{1}{\sqrt{2\pi\sigma^2_\alpha}} \exp\left[-\frac{1}{2\sigma^2_\alpha}(c_{ij} - \delta_{c1}Y_{ij0} - \overline{z}_{ij}\delta_{c2})^2\right]\right\} \\
&*\prod_{i=1}^{I}\prod_{t=t^0_i}^{t^1_i}\left\{\frac{1}{\sqrt{2\pi\sigma^2_\zeta}} \exp\left[-\frac{1}{2\sigma^2_\zeta}(d_{it} - \overline{z}_{it}\delta_d)^2\right]\right\} \\
&*\prod_{j=1}^{J}\prod_{t=t^0_j}^{t^1_j}\left\{\frac{1}{\sqrt{2\pi\sigma^2_\upsilon}} \exp\left[-\frac{1}{2\sigma^2_\upsilon}(e_{jt} - \overline{z}_{jt}\delta_e)^2\right]\right\},
\end{aligned}
\tag{1.4}
$$

where I (J) is the number of exporters (importers), J_i is the number of destinations for each exporter i, t^0_{ij} and t^1_{ij} are the second and last time periods where I have data for country pair ij,[7] $t^0_{i(j)}$ and $t^1_{i(j)}$ are the second and last time periods where I have data on exporter (importer) i (j), $\beta = (\theta', \rho)'$, $\delta = (\delta_{c1}, \delta'_{c2}, \delta'_d, \delta'_e)'$, $\sigma^2 = (\sigma^2_\varepsilon, \sigma^2_\alpha, \sigma^2_\zeta, \sigma^2_\upsilon)'$ and $w_{ijt} = \left(z'_{ijt}, \log(Y_{ijt-1} + \tau)\right)'$.[8] Since I do not observe the latent variables V^*_{ijt}, c_{ij}, d_{it} and e_{jt} and integration over these variables will produce an analytically intractable posterior function, direct implementation of Bayesian MCMC would be difficult. Instead, I adopt the data augmentation approach suggested by Albert and Chib (1993), where the latent variables V^*_{ijt}, c_{ij}, d_{it} and e_{jt} are explicitly included in the MCMC iterations and are updated at each step. Another advantage of the data augmentation technique is that with the presence of V^*_{ijt}, c_{ij}, d_{it} and e_{jt}, updating the main parameters of interest, β, becomes similar to the standard posterior updating for simple linear panel data models and therefore straightforward to implement.

The Bayesian algorithm is as follows,

1. Conditional on $\{c_{ij}\}_{\forall ij}$, $\{d_{it}\}^{t^1_i}_{t=t^0_i,\forall i}$, $\{e_{jt}\}^{t^1_j}_{t=t^0_j,\forall j}$, β, σ^2_ε, $\{Y_{ijt}\}^{t^1_{ij}}_{t=t^0_{ij},\forall ij}$ and $\{z_{ijt}\}^{t^1_{ij}}_{t=t^0_{ij},\forall ij}$,

[7] The first period is used for the initial condition.

[8] See Appendix A for derivation.

update $\left\{V^*_{ijt}\right\}_{t=t^0_{ij},\forall ij}^{t^1_{ij}}$ and τ in a block. Using the inverse gamma (N_τ, R_τ) prior for τ, that is, $\tau \tilde{} \tau^{-N_\tau-1}\exp(-R_\tau/\tau)$,

a update τ by drawing from the following conditional distribution[9]

$$\begin{aligned} & p(\tau|\{c_{ij}\}_{\forall ij},\{d_{it}\}_{t=t^0_i,\forall i}^{t^1_i},\{e_{jt}\}_{t=t^0_j,\forall j}^{t^1_j},\beta,\sigma^2_\varepsilon,\{Y_{ijt}\}_{t=t^0_{ij},\forall ij}^{t^1_{ij}},\{z_{ijt}\}_{t=t^0_{ij},\forall ij}^{t^1_{ij}}) \\ = & \left\{\prod_{i=1}^{I}\prod_{j=1}^{J_i}\prod_{t=t^0_{ij}}^{t^1_{ij}} 1(Y_{ijt}>0)\tfrac{1}{(Y_{ijt}+\tau)}\exp\left\{-\tfrac{\sigma_\varepsilon^{-2}}{2}\left[\begin{array}{c}\log(Y_{ijt}+\tau)\\ -w_{ijt}\beta-c_{ij}-d_{it}-e_{jt}\end{array}\right]^2\right\}\right\} \\ * & \left\{\prod_{i=1}^{I}\prod_{j=1}^{J_i}\prod_{t=t^0_{ij}}^{t^1_{ij}} 1(Y_{ijt}=0)\Phi\left[\tfrac{\log(\tau)-w_{ijt}\beta-c_{ij}-d_{it}-e_{jt}}{\sigma_\varepsilon}\right]\right\} * \tau^{-N_\tau-1}\exp(-R_\tau\tau^{-1}). \end{aligned} \tag{1.5}$$

Since (1.5) does not have a closed form, I use the Metropolis-Hastings method to draw τ. As $\tau>0$, I use the log normal distribution as the proposal density, that is, $q(\tau|\tau_{s-1})=\frac{1}{\tau\sqrt{2\pi\sigma^2_\tau}}\exp\left[-\frac{1}{2\sigma^2_\tau}(\log\tau-\log\tau_{s-1})^2\right]$, where τ_{s-1} is the value of τ from the last iteration of the MCMC algorithm and σ^2_τ is a tuning parameter. Thus, I draw τ^* from $q(\tau|\tau_{s-1})$ and then calculate $\rho(\tau_{s-1},\tau^*)=\min\left(\frac{p(\tau^*|...)}{p(\tau_{s-1}|...)}\frac{q(\tau_{s-1}|\tau^*)}{q(\tau^*|\tau_{s-1})},1\right)$. Finally, τ is set as τ^* with probability of $\rho(\tau_{s-1},\tau^*)$ and set as τ_{s-1} with probability of $1-\rho(\tau_{s-1},\tau^*)$.

b update V^*_{ijt} $\forall ijt$ from a truncated normal distribution with mean $w_{ijt}\beta+c_{ij}+d_{it}+e_{jt}$ and variance σ^2_ε with truncation at $\log(\tau)$ from above if $Y_{ijt}=0$. If $Y_{ijt}>0$, simply set $V^*_{ijt}=\log(Y_{ijt}+\tau)$.

2. Conditional on $\left\{V^*_{ijt}\right\}_{t=t^0_{ij},\forall ij}^{t^1_{ij}}$, $\{c_{ij}\}_{\forall ij}$, $\{d_{it}\}_{t=t^0_i,\forall i}^{t^1_i}$, $\{e_{jt}\}_{t=t^0_j,\forall j}^{t^1_j}$, σ^2_ε, $\{Y_{ijt}\}_{t=t^0_{ij},\forall ij}^{t^1_{ij}}$ and $\{z_{ijt}\}_{t=t^0_{ij},\forall ij}^{t^1_{ij}}$, update β. Using the improper flat prior for β, update β from its posterior, which is a normal distribution with mean

$$\left(\sum_{i=1}^{I}\sum_{j=1}^{J_i}\sum_{t=t^0_{ij}}^{t^1_{ij}} w'_{ijt}w_{ijt}\right)^{-1}\left[\sum_{i=1}^{I}\sum_{j=1}^{J_i}\sum_{t=t^0_{ij}}^{t^1_{ij}} w'_{ijt}\left(V^*_{ijt}-c_{ij}-d_{it}-e_{jt}\right)\right]$$

and variance $\left(\sigma_\varepsilon^{-2}\sum_{i=1}^{I}\sum_{j=1}^{J_i}\sum_{t=t^0_{ij}}^{t^1_{ij}} w'_{ijt}w_{ijt}\right)^{-1}$.

3. Conditional on $\left\{V^*_{ijt}\right\}_{t=t^0_{ij},\forall ij}^{t^1_{ij}}$, $\{c_{ij}\}_{\forall ij}$, $\{d_{it}\}_{t=t^0_i,\forall i}^{t^1_i}$, $\{e_{jt}\}_{t=t^0_j,\forall j}^{t^1_j}$, β, $\{Y_{ijt}\}_{t=t^0_{ij},\forall ij}^{t^1_{ij}}$

[9]See Appendix A for derivation.

and $\{z_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$, update σ_ε^2. Using the inverse gamma $(N_\varepsilon, R_\varepsilon)$ prior for σ_ε^2, that is, $\sigma_\varepsilon^2 \tilde{} \sigma_\varepsilon^{2(-N_\varepsilon-1)} \exp\left(-R_\varepsilon/\sigma_\varepsilon^2\right)$, update σ_ε^2 from its posterior, which is an inverse gamma distribution with parameters $N_\varepsilon + \frac{N}{2}$ and $\left[\frac{\sum_{i,j,t=1}^{N}(V_{ijt}^* - w_{ijt}\beta - c_{ij} - d_{it} - e_{jt})^2}{2}\right] + R_\varepsilon$, where $N = \sum_{i=1}^{I}\sum_{j=1}^{J_i}\sum_{t=t_{ij}^0}^{t_{ij}^1} 1$, that is, the total number of observations in the dataset.

4. Conditional on $\left\{V_{ijt}^*\right\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$, $\{d_{it}\}_{t=t_i^0,\forall i}^{t_i^1}$, $\{e_{jt}\}_{t=t_j^0,\forall j}^{t_j^1}$, β, σ_ε^2, δ_c, σ_α^2, $\{Y_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$ and $\{z_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$, update $\{c_{ij}\}_{\forall ij}$. Each c_{ij} is updated by drawing from a normal distribution with mean $\frac{\sum_{t=t_{ij}^0}^{t_{ij}^1}\left(V_{ijt}^* - w_{ijt}\beta - d_{it} - e_{jt}\right) + \frac{\sigma_\varepsilon^2}{\sigma_\alpha^2}(\delta_{c1}Y_{ij0} + \delta_{c2}\overline{z}_{ij})}{\left(t_{ij}^1 - t_{ij}^0 + 1\right) + \frac{\sigma_\varepsilon^2}{\sigma_\alpha^2}}$ and variance $\frac{1}{\left(t_{ij}^1 - t_{ij}^0 + 1\right)\sigma_\varepsilon^{-2} + \sigma_\alpha^{-2}}$.

5. Conditional on $\{c_{ij}\}_{\forall ij}$, σ_α^2, $\{Y_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$ and $\{z_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$, update δ_c. Using the improper flat prior for δ_c, update δ_c from its posterior, which is a normal distribution with mean $\left(\sum_{i=1}^{I}\sum_{j=1}^{J_i} w_{0ij}' w_{0ij}\right)^{-1}\left(\sum_{i=1}^{I}\sum_{j=1}^{J_i} w_{0ij}' c_{ij}\right)$ and variance $\left(\sigma_\alpha^{-2}\sum_{i=1}^{I}\sum_{j=1}^{J_i} w_{0ij}' w_{0ij}\right)^{-1}$, where $w_{0ij} = (Y_{ij0}, \overline{z}_{ij})$.

6. Conditional on $\{c_{ij}\}_{\forall ij}$, δ_c, $\{Y_{ijt}\}_{\forall ijt}$ and $\{z_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$, update σ_α^2. Using the inverse gamma (N_c, R_c) prior for σ_α^2, that is, $\sigma_\alpha^2 \tilde{} \sigma_\alpha^{2(-N_c-1)} \exp\left(-R_c/\sigma_\alpha^2\right)$, update σ_α^2 from its posterior, which is an inverse gamma distribution with parameters $N_c + \frac{\sum_{i=1}^{I}\sum_{j=1}^{J_i} 1}{2}$ and $\left[\frac{\sum_{i=1}^{I}\sum_{j=1}^{J_i}(c_{ij} - \delta_{c1}Y_{ij0} - \delta_{c2}\overline{z}_{ij})^2}{2}\right] + R_c$.

7. Conditional on $\left\{V_{ijt}^*\right\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$, $\{c_{ij}\}_{\forall ij}$, $\{e_{jt}\}_{t=t_j^0,\forall j}^{t_j^1}$, β, σ_ε^2, δ_d, σ_ζ^2, $\{Y_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$ and $\{z_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$, update $\{d_{it}\}_{t=t_i^0,\forall i}^{t_i^1}$. Each d_{it} is updated by drawing from a normal distribution with mean $\frac{\sum_{j=1}^{J_{it}}\left(V_{ijt}^* - w_{ijt}\beta - c_{ij} - e_{jt}\right) + \frac{\sigma_\varepsilon^2}{\sigma_\zeta^2}\delta_d\overline{z}_{it}}{J_{it} + \frac{\sigma_\varepsilon^2}{\sigma_\zeta^2}}$ and variance $\frac{1}{J_{it}\sigma_\varepsilon^{-2} + \sigma_\zeta^{-2}}$ where J_{it} is the number of destinations for each i at time period t.

8. Conditional on $\{d_{it}\}_{t=t_i^0,\forall i}^{t_i^1}$, σ_ζ^2, $\{Y_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$ and $\{z_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$, update δ_d. Using the improper flat prior for δ_d, update δ_d from its posterior, which is a normal distribution with

mean $\left(\sum_{i=1}^{I}\sum_{t=t_i^0}^{t_i^1}\overline{z}'_{it}\overline{z}_{it}\right)^{-1}\left(\sum_{i=1}^{I}\sum_{t=t_i^0}^{t_i^1}\overline{z}'_{it}d_{it}\right)$ and variance $\left(\sigma_\zeta^{-2}\sum_{i=1}^{I}\sum_{t=t_i^0}^{t_i^1}\overline{z}'_{it}\overline{z}_{it}\right)^{-1}$.

9. Conditional on $\{d_{it}\}_{t=t_i^0,\forall i}^{t_i^1}$, δ_d, $\{Y_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$ and $\{z_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$, update σ_ζ^2. Using the inverse gamma (N_d, R_d) prior for σ_ζ^2, that is, $\sigma_\zeta^{2\sim}\sigma_\zeta^{2(-N_d-1)}\exp\left(-R_d/\sigma_\zeta^2\right)$, update σ_ζ^2 from its posterior, which is an inverse gamma distribution with parameters $N_d + \frac{\sum_{i=1}^{I}\sum_{t=t_i^0}^{t_i^1}1}{2}$ and $\left[\frac{\sum_{i=1}^{I}\sum_{t=t_i^0}^{t_i^1}(d_{it}-\overline{z}_{it}\delta_d)^2}{2}\right] + R_d$.

10. Conditional on $\left\{V_{ijt}^*\right\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$, $\{c_{ij}\}_{\forall ij}$, $\{d_{it}\}_{t=t_i^0,\forall i}^{t_i^1}$, β, σ_ε^2, δ_e, σ_v^2, $\{Y_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$ and $\{z_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$, update $\{e_{jt}\}_{t=t_j^0,\forall j}^{t_j^1}$. Each e_{jt} is updated by drawing from a normal distribution with mean $\frac{\sum_{i=1}^{I_{jt}}\left(V_{ijt}^*-w_{ijt}\beta-c_{ij}-d_{it}\right)+\frac{\sigma_\varepsilon^2}{\sigma_v^2}\overline{z}_{jt}\delta_e}{I_{jt}+\frac{\sigma_\varepsilon^2}{\sigma_v^2}}$ and variance $\frac{1}{I_{jt}\sigma_\varepsilon^{-2}+\sigma_v^{-2}}$ where I_{jt} is the number of origins for each j at time period t.

11. Conditional on $\{e_{jt}\}_{t=t_j^0,\forall j}^{t_j^1}$, σ_v^2, $\{Y_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$ and $\{z_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$, update δ_e. Using the improper flat prior for δ_e, update δ_e from its posterior, which is a normal distribution with mean $\left(\sum_{j=1}^{J}\sum_{t=t_j^0}^{t_j^1}\overline{z}'_{jt}\overline{z}_{jt}\right)^{-1}\left(\sum_{j=1}^{J}\sum_{t=t_j^0}^{t_j^1}\overline{z}'_{jt}e_{jt}\right)$ and variance $\left(\sigma_v^{-2}\sum_{j=1}^{J}\sum_{t=t_j^0}^{t_j^1}\overline{z}'_{jt}\overline{z}_{jt}\right)^{-1}$.

12. Conditional on $\{e_{jt}\}_{t=t_j^0,\forall j}^{t_j^1}$, δ_e, $\{Y_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$ and $\{z_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}$, update σ_v^2. Using the inverse gamma (N_e, R_e) prior for σ_v^2, that is, $\sigma_v^{2\sim}\sigma_v^{2(-N_e-1)}\exp\left(-R_e/\sigma_v^2\right)$, update σ_v^2 from its posterior, which is an inverse gamma distribution with parameters $N_e + \frac{\sum_{j=1}^{J}\sum_{t=t_j^0}^{t_j^1}1}{2}$ and $\left[\frac{\sum_{j=1}^{J}\sum_{t=t_j^0}^{t_j^1}(e_{jt}-\overline{z}_{jt}\delta_e)^2}{2}\right] + R_e$.

This completes my Bayesian estimation algorithm.

1.3.1 Marginal Effects

For nonlinear models, in addition to the estimation of parameters, obtaining the marginal effects is necessary to assess the effects of any change in the covariates on the dependent variable. This is important because it can be used to evaluate policies. Easy inference of the marginal effects is also one main advantage of the Bayesian method I propose in this chapter. The inference of the marginal effects becomes a by-product of the MCMC estimation procedure, and hence does not add in any additional computation burden.

For the dynamic panel data gravity model, the marginal effect of the observed trade flow in the last period on the expected value of the observed trade flow in the current period is

$$\frac{\partial E[Y_{ijt}|w_{ijt},c_{ij},d_{it},e_{jt}]}{\partial Y_{ijt-1}} = \left\{ \begin{array}{c} -\phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{\tau}{\sigma_\varepsilon} \\ +\exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right)\left[\begin{array}{c}\Phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right) \\ +\phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{1}{\sigma_\varepsilon}\end{array}\right] \end{array} \right\} \frac{\rho}{(Y_{ijt-1}+\tau)} \quad , \quad (1.6)$$

where $A_{ijt} \equiv \log(Y_{ijt-1}+\tau)\rho + z_{ijt}\theta + c_{ij} + d_{it} + e_{jt}$.[10] For a continuous variable $z_{ijt,k}$ in z_{ijt} with no interaction terms involved, the marginal effect is

$$\frac{\partial E[Y_{ijt}|w_{ijt},c_{ij},d_{it},e_{jt}]}{\partial z_{ijt,k}} = \left\{ \begin{array}{c} -\phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{\tau}{\sigma_\varepsilon} \\ +\exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right)\left[\begin{array}{c}\Phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right) \\ +\phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{1}{\sigma_\varepsilon}\end{array}\right] \end{array} \right\} * \theta_k \quad . \quad (1.7)$$

For a discrete variable $z_{ijt,k}$ in z_{ijt} with no interaction terms involved, the marginal effect is the difference between the values $E[Y_{ijt}|Y_{ijt-1}, z_{ijt}, c_{ij}, d_{it}, e_{jt}]$ takes when $z_{ijt,k}=1$ and $z_{ijt,k}=0$, where

$$E[Y_{ijt}|w_{ijt},c_{ij},d_{it},e_{jt}] = \Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right) * \left[\exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right) * \frac{\Phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)}{\Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)} - \tau\right] \quad . \quad (1.8)$$

In the Bayesian framework, the inference of marginal effects comes as a by-product during the estimation of the model parameters. More specifically, I can obtain the summaries of the marginal effects conditional on the observed data, but marginalized over all the unknown model parameters.[11] To fix ideas, denote any of the marginal effect above as m_{ijt} and by definition, the posterior density of m_{ijt} conditional on the observed data, but marginalized over the unknown

[10] See Appendix A for derivations.

[11] Chib and Hamilton (2002) use this approach to obtain the average treatment effects.

parameters, is

$$\pi(m_{ijt}|\text{data}) = \int \pi(m_{ijt}|\text{data, parameters})d\pi(\text{parameters}|\text{data}).$$

A sample of m_{ijt} from its posterior distribution, $\{m_{ijt}^{(g)}\}$, $g = 1, ..., G$, can be produced by the method of composition using the draws of parameters from the MCMC algorithm described above. For example, $\frac{\partial E[Y_{ijt}|w_{ijt},c_{ij},d_{it},e_{jt}]}{\partial Y_{ijt-1}}^{(g)}$ is

$$\left\{ \begin{array}{c} -\phi\left(\frac{A_{ijt}^{(g)}-\log\tau^{(g)}}{\sigma_{\varepsilon}^{(g)}}\right)\frac{\tau^{(g)}}{\sigma_{\varepsilon}^{(g)}} \\ +\exp\left(A_{ijt}^{(g)}+\frac{\sigma_{\varepsilon}^{(g)2}}{2}\right)\left[\begin{array}{c} \Phi\left(\sigma_{\varepsilon}^{(g)}+\frac{A_{ijt}^{(g)}-\log\tau^{(g)}}{\sigma_{\varepsilon}^{(g)}}\right) \\ +\phi\left(\sigma_{\varepsilon}^{(g)}+\frac{A_{ijt}^{(g)}-\log\tau^{(g)}}{\sigma_{\varepsilon}^{(g)}}\right)\frac{1}{\sigma_{\varepsilon}^{(g)}} \end{array}\right] \end{array} \right\} \frac{\rho^{(g)}}{(Y_{ijt-1}+\tau^{(g)})},$$

where $\log(Y_{ijt-1}+\tau^{(g)})\rho^{(g)} + z_{ijt}\theta^{(g)} + c_{ij}^{(g)} + d_{it}^{(g)} + e_{jt}^{(g)}$.

1.4 The Application: Re-examining the Effect of GATT/WTO on Trade

The General Agreement on Tariffs and Trade (GATT) was established to promote international trade after the Second World War in 1947, and its successor, the World Trade Organization (WTO), was established in 1995. The GATT/WTO has grown in membership from the original 23 GATT countries to 159 countries (as of March 2, 2013). Through the eight rounds of multilateral trade negotiations conducted under the auspices of GATT/WTO, the average tariff on manufactured goods has fallen from about 40 percent to about 4 percent.

Many economists believe that multilateral trade agreements such as the GATT/WTO promote international trade. However, Rose (2004) shows that it is not clear that the GATT/WTO has increased international trade, which runs counter to the conventional wisdom. However, some recent empirical studies (e.g., Subramanian and Wei 2007; Tomz, Goldsetin and Rivers 2007; Liu 2009; Grant and Boys 2011) find that GATT/WTO indeed has had a positive effect on trade flow. In most specifications used in these studies, the lagged dependent variable is not included as a control variable. In a few specifications, a dynamic model is estimated on the subsample of data with positive trade volume, thus suffering from sample selection bias. To the best of my knowledge, no study has ever estimated the effect of GATT/WTO on trade using a specification that controls for the lagged dependent variable and sample selection at the same time. I aim to fill this gap by applying the empirical model developed above to re-examine the effect of GATT/WTO on trade.

1.4.1 Data and Specification

My data are the same as those used by Liu (2009), which I downloaded from Liu's website.[12] This is the most comprehensive bilateral trade dataset to date, covering 208 countries over 55 years from 1948 to 2002. The unit of observation is export from country i to country j in year t. In total, there are 1,075,608 observations. Table 1.1 provides the list and the definitions of variables used in my estimation. See Liu (2009) for their sources. Most of the variables are self-explanatory, except the remoteness and hostility variables. The remoteness variable, REM_{ijt}, is defined as $REM_{ijt} = \left(\frac{\sum_{m \neq i} \text{Distance}_{im} GDP_{mt}}{\sum_{m \neq i} GDP_{mt}}\right)\left(\frac{\sum_{m \neq j} \text{Distance}_{jm} GDP_{mt}}{\sum_{m \neq j} GDP_{mt}}\right)$. The first term is country i's remoteness in year t, which is defined as the GDP weighted distance to all of its trading partners in year t, and the second term is country j's remoteness in year t. REM_{ijt}, which is the product of country i and country j's remoteness, reflects the remoteness of the country pair ij in year t. The higher the value of this variable, the lower the expected trade flow between the two countries. The hostility variable, HOS_{ij}, represents the intensity of military conflict between i and j. The hostility level of an incident is an ordinal number from 0 (no conflict) to 5 (war) with a higher number representing greater hostility. Because the effect of military conflict is persistent, Liu (2009) uses the average hostility level over 1946-2001. Table 1.2 provides the summary statistics for all the variables. It is also worth mentioning that the many zeros for the dependent variable is an important feature of this dataset. Of the 1,075,608 observations, the observed trade flow is 0 for 537,100 or 49.9% of the observations. Therefore, it is important to use an estimation method that can accommodate this important feature of the data.

In more detail, I use the following variables (z_{ijt} variables in (1.1)) to control for exporter and importer characteristics. These include log of exporter's and importer's GDP in year t ($\log GDP_{it}$, $\log GDP_{jt}$), log of exporter's and importer's GDP per capita in year t ($\log PerGDP_{it}$, $\log PerGDP_{jt}$), log of distance ($\log Dist_{ij}$), log of exporter's area ($\log Area_i$), log of importer's area ($\log Area_j$), whether i and j share a common border (BOR_{ij}), the number of landlocked countries for the ij pair (LOC_{ij}), the number of island countries for the ij pair (ISL_{ij}), whether i and j use the same language (LAN_{ij}), whether i and j have the same religion (REL_{ij}), whether i has ever been a colony of j (COL_{ij}), whether i has ever been a colonizer of j (COZ_{ij}), whether i is currently a colony of j ($CCOL_{ijt}$), whether i is currently a colonizer of j ($CCOZ_{ijt}$), whether i and j have ever been colonized by the same country (COM_{ij}), the remoteness of the country pair ij in year t (REM_{ijt}), whether both i and j are members of GATT/WTO in year t ($BOTH_{ijt}$), whether either i or j is a member of GATT/WTO in year t (ONE_{ijt}), whether i and j are members of the same regional trade agreement in year t (RTA_{ijt}), whether i offers Generalized System of Preference (GSP) to j in year t ($EIGSP_{ijt}$),

[12] I applaud Liu's generosity for posting his dataset online.

whether j offers Generalized System of Preference (GSP) to i in year t ($IEGSP_{ijt}$), whether i and j are members of the same currency union in year t (CU_{ijt}), whether i and j have an alliance relationship in year t (ALI_{ijt}) and the average hostility level between i and j from 1948 to 2001 (HOS_{ij}). The two variables of key interest are $BOTH_{ijt}$ and ONE_{ijt}.

Regarding the specification for variables in $\overline{z}_{ij}$, in principle, I can include the average across time for any variable in z_{ijt} that is not time constant. In practice, however, this will result in many variables that are highly correlated with the original variables in z_{ijt} and the Bayesian estimation algorithm does not converge due to the multicollinearity problem. This is due to the fact that for many variables in z_{ijt} that vary over time, the variation is small. As a result, I only include the following variables in $\overline{z}_{ij}$. These include $\overline{BOTH}_{ij}$, $\overline{ONE}_{ij}$ and $\overline{RTA}_{ij}$, where $\overline{BOTH}_{ij} = \frac{1}{(t^1_{ij}-t^0_{ij}+1)} \sum_{t=t^0_{ij}}^{t^1_{ij}} BOTH_{ijt}$ and other terms are similarly defined. For the same reason, I include the following variables in $\overline{z}_{it}$: $\overline{\log GDP}^{IMP}_t$, $\overline{\log Dist}_i$, $\overline{BOR}_i$, $\overline{LAN}_i$, $\overline{REL}_i$, $\overline{COL}_i$, $\overline{COZ}_i$, $\overline{CCOZ}_{it}$, $\overline{COM}_i$, $\overline{BOTH}_{it}$, $\overline{ONE}_{it}$, $\overline{RTA}_{it}$, $\overline{CU}_{it}$, $\overline{ALI}_{it}$ and $\overline{HOS}_i$, where $\overline{\log GDP}^{IMP}_t = \frac{1}{J_{it}} \sum_{j=1}^{J_{it}} \log GDP_{jt}$, J_{it} is the number of countries country i exports in year t and other terms are similarly defined, and the following variables in $\overline{z}_{jt}$: $\overline{\log GDP}^{EXP}_t$, $\overline{\log Dist}_j$, $\overline{BOR}_j$, $\overline{LAN}_j$, $\overline{REL}_j$, $\overline{COL}_j$, $\overline{COZ}_j$, $\overline{CCOL}_{jt}$, $\overline{COM}_j$, $\overline{BOTH}_{jt}$, $\overline{ONE}_{jt}$, $\overline{RTA}_{jt}$, $\overline{CU}_{jt}$, $\overline{ALI}_{jt}$ and $\overline{HOS}_j$, where $\overline{\log GDP}^{EXP}_t = \frac{1}{I_{jt}} \sum_{i=1}^{I_{jt}} \log GDP_{it}$, I_{jt} is the number of countries country j imports in year t and other terms are similarly defined.

1.4.2 Estimation Results

The hyperparameters N_τ, N_ε, N_c, N_d, N_e, R_τ, R_ε, R_c, R_d and R_e are all chosen to be 1 to reflect my weak prior information on the corresponding parameters. The tuning parameter σ^2_τ is set to be 0.0001 to obtain a reasonable acceptance rate in the MH step within the Gibbs Sampler. I run the MCMC for 30,000 iterations, with an initial 15,000 burn-in period. With the current setting of the tuning parameter, the acceptance rate is 35.15% for sampling τ^* in step 1.a of the MCMC algorithm above. The trace plots for the coefficients θ in (1.1) are displayed in Figure 1.1 - 1.4.[13] The posterior distributions for the coefficients are displayed in Figure 1.5 - 1.8. The histograms of all the posterior distributions are similar to that of a normal distribution. I also use the Geweke's diagnostic method to check for convergence (see Table 1.9).[14][15] For each

[13] Trace plots and posterior distributions for parameters in (1.2) and (1.3) are omitted for the sake of brevity. They are available upon request.

[14] Geweke (1992) develops a convergence diagnostic for the Markov chain based on a test for equality of means of the first 10% and the last 50% of the chain. The test statistic is a standard Z score with the standard errors adjusted for autocorrelation. The large absolute value of Geweke's statistic indicates that the chain has not converged.

[15] Most of the MCMC algorithm seems to be converging. However, $BOTH_{ijt}$ and ONE_{ijt} converge only slowly.

coefficient, the mean, standard deviation and 95% credible intervals of its posterior distribution are reported in Table 1.3. The mean, standard deviation and 95% credible intervals of the posterior distribution for the corresponding marginal effects are reported in Table 1.4.

Several interesting results in Table 1.3 are worth mentioning. First, even after controlling for many covariates and three sets of unobserved effects, the lagged dependent variable is still very important. The point estimate for ρ is 0.7732 with a standard deviation of 0.0011. This indicates that the trade flow in the current period is highly influenced by the trade flow in the previous year. From the marginal effect estimate in Table 1.4, I can see that a \$1 billion increase in the trade flow in the previous period will increase the trade flow in the current period by \$0.6617 billion. Therefore, there is also persistence in the aggregate trade flow data, consistent with the results from micro- or firm-level studies discussed above. This lends further support to the idea that the lagged dependent variable is an important variable that should be included in gravity model estimation. Second, the point estimate for τ is 0.0003 with a standard deviation very close to 0. This means that the threshold exists and the magnitude of the trade that is lost in transit is about \$0.0003 billion. The average trade flow in my sample is \$0.1077 billion (see Table 1.2). Therefore, this indicates that on average, about 0.28% of the trade flow is lost in transit. Third, regarding the two variables of primary interest, $BOTH_{ijt}$ and ONE_{ijt}, my results differ from those of Liu (2009). The point estimate for $BOTH_{ijt}$ is -0.0155 with a large standard deviation of 0.0585. Similarly, the point estimate for ONE_{ijt} is 0.0011 with a large standard deviation of 0.0297. Considering the posterior distributions of coefficients for $BOTH_{ijt}$ and ONE_{ijt} in Figure 1.7, these results imply that GATT/WTO does not appear to have an effect on trade flow. This result is consistent with Rose (2004) and Roy (2011), but opposite to studies by Subramanian and Wei (2007), Tomz, Goldsetin and Rivers (2007) and Liu (2009). The difference between my result here and those of Subramanian and Wei (2007) and Tomz, Goldsetin and Rivers (2007) might be due to differences in the datasets being used. However, I use the same dataset Liu (2009) used and the fact that my result also differs from his lends support to the notion that whether the lagged dependent variable is included in gravity model estimation or not can lead to quite different conclusions.

Most of my results for other coefficients have the expected signs and are consistent with those found in the literature. Trade promoting variables include larger size of an economy (GDP), higher income (GDP per capita), sharing a common border, the same language, the same religion, having a colonial relationship, being members of the same regional trade agreement, giving or given Generalized System of Preference, being members of the same currency union and being allies. Trade barrier variables include distance, being landlocked, being remote from its trading partners and having a hostile relationship. Being an island country appears to have a positive effect on trade.

1.4.3 Model Selection

Although there are theoretical justifications as well as micro- or firm-level empirical evidence for the dynamic gravity model, whether the dynamic gravity model fits the aggregate data better than the static one is an empirical question. To answer this question, I conduct model selection using the out-of-sample mean squared error of prediction (MSEP) test. The static gravity model is the same as its dynamic counterpart above except that $\log(Y_{ijt-1}+\tau)\rho$ is removed from (1.1) and $\delta_{c1}Y_{ij0}$ is dropped from (1.2). I estimate both models using data from 1948 to 2001 and then compute the out-of-sample MSEP for each model using data for the year 2002 and the parameter estimates. More specifically, the out-of-sample MSEP is computed using $\frac{1}{I}\sum_{i=1}^{I}\frac{1}{J_i}\sum_{j=1}^{J_i}\left(\widehat{Y}_{ij2002}-Y_{ij2002}\right)^2$, where $\widehat{Y}_{ij2002}$ is the simulated version of the right hand side of (1.8),

$$\widehat{Y}_{ij2002}=\frac{1}{S}\sum_{s=1}^{S}\left\{\Phi\left(\frac{A_{ij2002}^{(s)}-\log\widehat{\tau}}{\sigma_\varepsilon}\right)*\left[\exp\left(A_{ij2002}^{(s)}+\frac{\widehat{\sigma}_\varepsilon^2}{2}\right)*\frac{\Phi\left(\widehat{\sigma}_\varepsilon+\frac{A_{ij2002}^{(s)}-\log\widehat{\tau}}{\widehat{\sigma}_\varepsilon}\right)}{\Phi\left(\frac{A_{ij2002}^{(s)}-\log\widehat{\tau}}{\widehat{\sigma}_\varepsilon}\right)}-\widehat{\tau}\right]\right\},$$

where $A_{ij2002}^{(s)}=\log\left(Y_{ij2001}+\widehat{\tau}\right)\widehat{\rho}+z_{ij2002}\widehat{\theta}+c_{ij}^{(s)}+d_{i2002}^{(s)}+e_{j2002}^{(s)}$, $c_{ij}^{(s)}\tilde{}N(\widehat{\delta}_{c1}Y_{ij0}+\overline{z}_{ij}\widehat{\delta}_{c2},\widehat{\sigma}_\alpha^2)$, $d_{i2002}^{(s)}\tilde{}N(\overline{z}_{i2002}\widehat{\delta}_d,\widehat{\sigma}_\zeta^2)$ and $e_{j2002}^{(s)}\tilde{}N(\overline{z}_{j2002}\widehat{\delta}_e,\widehat{\sigma}_v^2)$. The model with a lower MSEP fits the data better.

The estimation and prediction results using the dynamic model are reported in Table 1.5. Because the only data not used in estimation are for the year 2002, the estimation results are almost identical to those in Table 1.3. The calculated MSEP is 11.82. Table 1.7 reports the estimation results from the static version of the model. The calculated MSEP is 596.82. This means that the dynamic gravity model fits the data better than the static gravity model. Compared with results in Table 1.6, the magnitudes of the marginal effects in Table 1.8 are about 4 to 5 times of those in Table 1.6. This is because the estimates from the static model reflect the long-run equilibrium effects of the variables, while the estimates in the dynamic model reflect the short-run effects of the variables. The estimate for the lagged dependent variable ρ in Table 1.3 is 0.7732. Because my dynamic model is an AR(1) model, this implies that the long-run effects are about $\frac{1}{1-\rho}=4.4$ times of the short-run effects, which is consistent with what I find.

Another interesting finding is that GATT/WTO membership appears to have a positive effect on trade in the static model, which is consistent with Liu (2009). And, comparing the results of the dynamic gravity model (Table 1.5) and static gravity model (Table 1.7), I find that the two models have different results for the signs of estimates for three variables, which are $CCOL_{ijt}$, $EIGSP_{ijt}$ and $IEGSP_{ijt}$. All signs of estimates for these three variables in the

dynamic gravity model are positive. However, in the static gravity model, the signs of estimates for $CCOL_{ijt}$ and $EIGSP_{ijt}$ are negative and the sign of the estimate for $IEGSP_{ijt}$ is not clear. This shows that not including the lagged dependent variable might lead to an omitted variable problem and a different result. And, the remaining difference between my result here and that of Liu (2009) is likely to be driven by the fact that Liu (2009) only includes one set of unobserved effects, that is, c_{ij}, in his gravity model, together with yearly dummies. Instead of the yearly dummies, I include time-varying country-specific unobserved effects d_{it} and e_{jt} in my gravity model. d_{it} and e_{jt} capture unobserved yearly effects that can vary across trading partners, while the yearly dummies can only capture unobserved yearly effects that are the same for all countries. I believe that this is the driving force for the difference between my results and those of Liu (2009). This shows the importance of controlling for multiple sets of unobserved effects and especially the multilateral resistance terms in gravity model estimation.

1.5 Conclusion

In this chapter, I develop a Bayesian estimation method for inferring a dynamic panel data gravity model. My method deals with the many zeros problem and at the same time allows for lagged dependent variables and multiple sets of unobserved effects. I apply the Bayesian estimation algorithm to re-examine the effect of GATT/WTO membership on trade. I find that the dynamic gravity model fits the data better than the static version of the same model, and trade flow in the previous period has a large and positive effect on trade flow in the current period. I also find that GATT/WTO membership does not appear to have an effect on trade flow. This result is consistent with the findings of Rose (2004), but not with those of Liu (2009), who uses the same dataset. This shows the importance of including lagged dependent variables and multiple sets of unobserved effects in gravity model estimation.

Table 1.1: Variable Definitions

Variable	Definition
log $GDP_{i(j)t}$	log of real GDP of exporter i (importer j) in year t (1995 real dollars)
log $PerGDP_{it}$	log of real GDP per capita of i (j) in year t (1995 real dollars)
log $Dist_{ij}$	log of distance between i and j (km)
log $Area_{i(j)}$	log of area of i (j) (sq km)
BOR_{ij}	i and j share the border
LOC_{ij}	the number of landlocked countries for the ij pair
ISL_{ij}	the number of island countries for the ij pair
LAN_{ij}	i and j use the same language
REL_{ij}	i and j have the same religion
COL_{ij}	i has ever been a colony of j
COZ_{ij}	i has ever been a colonizer of j
$CCOL_{ij}$	i is currently a colony of j
$CCOZ_{ij}$	i is currently a colonizer of j
COM_{ij}	i and j have ever been colonized by the same country
REM_{ijt}	Remoteness of ij pair in year t
$BOTH_{ijt}$	Both i and j are members of GATT/WTO in year t
ONE_{ijt}	Either i or j is a member of GATT/WTO in year t
RTA_{ijt}	i and j are members of the same regional trade agreement in year t
$EIGSP_{ijt}$	i offers GSP (Generalized System of Preference) to j in year t
$IEGSP_{ijt}$	j offers GSP (Generalized System of Preference) to i in year t
CU_{ijt}	i and j are in same currency union in year t
ALI_{ijt}	i and j have an alliance relationship
HOS_{ij}	the average hostility level between i and j over 1946-2001
Y_{ijt}	Export from i to j in year t (1995 real billion dollars)

Table 1.2: Summary Statistics

	Mean	Std.Dev.	Min	Max		Mean	Std.Dev	Min	Max
log GDP_{it}	9.9451	2.1834	0.12	16.07	COM_{ij}	0.1635	0.3698	0	1
log GDP_{jt}	9.9058	2.1951	0.12	16.07	REM_{ijt}	0.8256	1.7066	0	4.51
log $PerGDP_{it}$	1.3233	1.0759	-1.97	3.90	$BOTH_{ijt}$	0.3266	0.4690	0	1
log $PerGDP_{jt}$	1.3289	1.0738	-1.97	3.90	ONE_{ijt}	0.4703	0.4991	0	1
log $Dist_{ij}$	8.7041	0.7881	4.15	9.91	RTA_{ijt}	0.0648	0.2462	0	1
log $Area_i$	11.7800	2.5056	3.04	16.92	$EIGSP_{ijt}$	0.0906	0.2871	0	1
log $Area_j$	11.7486	2.5221	3.04	16.92	$IEGSP_{ijt}$	0.0895	0.2854	0	1
BOR_{ij}	0.0218	0.1459	0	1	CU_{ijt}	0.0239	0.1527	0	1
LOC_{ij}	0.2930	0.4990	0	2	ALI_{ijt}	0.0667	0.2496	0	1
ISL_{ij}	0.4000	0.5718	0	2	HOS_{ij}	0.0121	0.0997	0	3.33
LAN_{ij}	0.1150	0.3190	0	1	Y_{ijt}	0.1077	1.4512	0	211.10
REL_{ij}	0.5084	0.4999	0	1					
COL_{ij}	0.0071	0.0840	0	1					
COZ_{ij}	0.0070	0.0837	0	1					
$CCOL_{ij}$	0.0014	0.0368	0	1					
$CCOZ_{ij}$	0.0014	0.0368	0	1					

Note: Number of observations: 1,075,608

Table 1.3: Posterior Distributions of Coefficients

	Coefficient		Credible Interval			Coefficient		Credible Interval	
	Mean	Std.Dev.	Lower	Upper		Mean	Std.Dev	Lower	Upper
log GDP_{it}	0.2777	0.0049	0.2680	0.2870	COM_{ij}	0.2029	0.0106	0.1822	0.2241
log GDP_{jt}	0.2253	0.0062	0.2132	0.2364	REM_{ijt}	-0.0259	0.0024	-0.0304	-0.0212
log $PerGDP_{it}$	0.0849	0.0067	0.0715	0.0977	$BOTH_{ijt}$	-0.0155	0.0585	-0.1324	0.0969
log $PerGDP_{jt}$	0.1068	0.0094	0.0879	0.1242	ONE_{ijt}	0.0011	0.0297	-0.0600	0.0572
log $Dist_{ij}$	-0.4093	0.0058	-0.4204	-0.3979	RTA_{ijt}	0.0294	0.0064	0.0168	0.0418
log $Area_i$	-0.0327	0.0035	-0.0395	-0.0257	$EIGSP_{ijt}$	0.0241	0.0084	0.0075	0.0404
log $Area_j$	-0.0412	0.0042	-0.0500	-0.0332	$IEGSP_{ijt}$	0.0451	0.0091	0.0273	0.0631
BOR_{ij}	0.1950	0.0225	0.1515	0.2403	CU_{ijt}	0.4011	0.0161	0.3690	0.4318
LOC_{ij}	-0.0582	0.0106	-0.0785	-0.0374	ALI_{ijt}	0.0395	0.0087	0.0225	0.0564
ISL_{ij}	0.0420	0.0132	0.0166	0.0690	HOS_{ij}	-0.2211	0.0323	-0.2832	-0.1575
LAN_{ij}	0.1464	0.0126	0.1227	0.1707	ρ	0.7732	0.0011	0.7711	0.7755
REL_{ij}	0.0503	0.0070	0.0367	0.0639	τ	0.0003	1.7×10^{-6}	0.0003	0.0003
COL_{ij}	0.3476	0.0391	0.2702	0.4235	σ^2_ε	0.7448	0.0024	0.7401	0.7496
COZ_{ij}	0.2428	0.0408	0.1599	0.3194	σ^2_α	0.1771	0.0023	0.1725	0.1814
$CCOL_{ij}$	0.1836	0.0373	0.1091	0.2556	σ^2_ζ	0.1044	0.0025	0.0997	0.1094
$CCOZ_{ij}$	0.4032	0.0379	0.3313	0.4799	σ^2_ν	0.2650	0.0053	0.2543	0.2751
MH Acc Rate					35.15%				
Num of Iters					30,000(Burn-in rate 50%)				

Note: Hyperparameters: N_τ=N_ε=N_c=N_d=N_e=1, R_τ=R_ε=R_c=R_d=R_e=1

Tuning parameter: σ^2_τ=0.0001

Lower bound and upper bound of 95% credible intervals for the parameters

Table 1.4: Posterior Distributions of Marginal Effects

	Marginal Effects		Credible Interval			Marginal Effects		Credible Interval	
	Mean	Std.Dev.	Lower	Upper		Mean	Std.Dev	Lower	Upper
log GDP_{it}	0.0427	0.0008	0.0410	0.0443	COM_{ij}	0.0338	0.0019	0.0300	0.0377
log GDP_{jt}	0.0346	0.0010	0.0326	0.0364	REM_{ijt}	-0.0040	0.0004	-0.0049	-0.0033
log $PerGDP_{it}$	0.0130	0.0010	0.0110	0.0150	$BOTH_{ijt}$	-0.0026	0.0091	-0.0212	0.0145
log $PerGDP_{jt}$	0.0164	0.0014	0.0136	0.0192	ONE_{ijt}	8.8×10^{-6}	0.0046	-0.0097	0.0086
log $Dist_{ij}$	-0.0629	0.0011	-0.0650	-0.0609	RTA_{ijt}	0.0045	0.0010	0.0026	0.0065
log $Area_{i}$	-0.0050	0.0005	-0.0061	-0.0040	$EIGSP_{ijt}$	0.0037	0.0013	0.0012	0.0063
log $Area_{j}$	-0.0063	0.0007	-0.0077	-0.0051	$IEGSP_{ijt}$	0.0071	0.0015	0.0043	0.0099
BOR_{ij}	0.0318	0.0039	0.0240	0.0394	CU_{ijt}	0.0753	0.0037	0.0681	0.0827
LOC_{ij}	-0.0087	0.0016	-0.0117	-0.0057	ALI_{ijt}	0.0061	0.0013	0.0034	0.0086
ISL_{ij}	0.0065	0.0021	0.0026	0.0107	HOS_{ij}	-0.0340	0.0050	-0.0434	-0.0240
LAN_{ij}	0.0236	0.0021	0.0197	0.0278	ρ	0.6617	0.0015	0.6587	0.6647
REL_{ij}	0.0077	0.0011	0.0056	0.0098					
COL_{ij}	0.0632	0.0083	0.0470	0.0797					
COZ_{ij}	0.0420	0.0079	0.0267	0.0574					
$CCOL_{ij}$	0.0311	0.0069	0.0178	0.0448					
$CCOZ_{ij}$	0.0764	0.0087	0.0586	0.0929					
MH Acc Rate	35.15%								
Num of Iters	30,000(Burn-in rate 50%)								

Note: Hyperparameters: $N_{\tau}=N_{\varepsilon}=N_{c}=N_{d}=N_{e}=1$, $R_{\tau}=R_{\varepsilon}=R_{c}=R_{d}=R_{e}=1$

Tuning parameter: $\sigma_{\tau}^{2}=0.0001$

Lower bound and upper bound of 95% credible intervals for the parameters

Table 1.5: Posterior Distributions of Coefficients

	Coefficient		Credible Interval			Coefficient		Credible Interval	
	Mean	Std.Dev.	Lower	Upper		Mean	Std.Dev	Lower	Upper
log GDP_{it}	0.2765	0.0047	0.2674	0.2857	COM_{ij}	0.2055	0.0110	0.1848	0.2273
log GDP_{jt}	0.2218	0.0067	0.2086	0.2351	REM_{ijt}	-0.0263	0.0024	-0.0310	-0.0217
log $PerGDP_{it}$	0.0853	0.0066	0.0723	0.0980	$BOTH_{ijt}$	-0.0329	0.0587	-0.1376	0.0913
log $PerGDP_{jt}$	0.1121	0.0097	0.0932	0.1310	ONE_{ijt}	-0.0072	0.0299	-0.0609	0.0561
log $Dist_{ij}$	-0.4115	0.0056	-0.4223	-0.4008	RTA_{ijt}	0.0310	0.0067	0.0179	0.0441
log $Area_i$	-0.0330	0.0034	-0.0399	-0.0266	$EIGSP_{ijt}$	0.0229	0.0087	0.0056	0.0398
log $Area_j$	-0.0417	0.0046	-0.0508	-0.0329	$IEGSP_{ijt}$	0.0461	0.0093	0.0280	0.0644
BOR_{ij}	0.1933	0.0229	0.1490	0.2388	CU_{ijt}	0.3999	0.0161	0.3689	0.4315
LOC_{ij}	-0.0542	0.0112	-0.0747	-0.0318	ALI_{ijt}	0.0376	0.0090	0.0205	0.0554
ISL_{ij}	0.0422	0.0144	0.0122	0.0695	HOS_{ij}	-0.2218	0.0313	-0.2834	-0.1615
LAN_{ij}	0.1451	0.0125	0.1203	0.1693	ρ	0.7727	0.0011	0.7704	0.7748
REL_{ij}	0.0501	0.0072	0.0369	0.0652	τ	0.0004	1.9×10^{-6}	0.0003	0.0004
COL_{ij}	0.3464	0.0408	0.2686	0.4261	σ^2_ε	0.7395	0.0025	0.7347	0.7443
COZ_{ij}	0.2473	0.0397	0.1662	0.3217	σ^2_α	0.1770	0.0022	0.1728	0.1814
$CCOL_{ij}$	0.1783	0.0377	0.1026	0.2501	σ^2_ζ	0.1049	0.0024	0.1003	0.1097
$CCOZ_{ij}$	0.3955	0.0379	0.3229	0.4716	σ^2_ν	0.2672	0.0055	0.2569	0.2783
MH Acc Rate					34.68%				
MSEP					11.8203				
Num of Iters					30,000(Burn-in rate 50%)				

Note: Hyperparameters: N_τ=N_ε=N_c=N_d=N_e=1, R_τ=R_ε=R_c=R_d=R_e=1; Tuning parameter: σ^2_τ=0.0001

Lower bound and upper bound of 95% credible intervals for the parameters

Estimation results are from estimation using data from 1948 to 2001.

Data for 2002 used for out-of-sample model selection.

Table 1.6: Posterior Distributions of Marginal Effects

	Marginal Effects		Credible Interval			Marginal Effects		Credible Interval	
	Mean	Std.Dev.	Lower	Upper		Mean	Std.Dev	Lower	Upper
log GDP_{it}	0.0414	0.0008	0.0399	0.0430	COM_{ij}	0.0334	0.0020	0.0298	0.0374
log GDP_{jt}	0.0332	0.0010	0.0312	0.0353	REM_{ijt}	-0.0039	0.0004	-0.0046	-0.0032
log $PerGDP_{it}$	0.0128	0.0010	0.0108	0.0147	$BOTH_{ijt}$	-0.0052	0.0090	-0.0214	0.0134
log $PerGDP_{jt}$	0.0168	0.0015	0.0140	0.0197	ONE_{ijt}	-0.0013	0.0046	-0.0098	0.0081
log $Dist_{ij}$	-0.0617	0.0010	-0.0636	-0.0597	RTA_{ijt}	0.0047	0.0010	0.0028	0.0067
log $Area_i$	-0.0049	0.0005	-0.0060	-0.0040	$EIGSP_{ijt}$	0.0035	0.0013	0.0008	0.0061
log $Area_j$	-0.0062	0.0007	-0.0076	-0.0049	$IEGSP_{ijt}$	0.0070	0.0014	0.0042	0.0098
BOR_{ij}	0.0308	0.0039	0.0231	0.0384	CU_{ijt}	0.0732	0.0036	0.0663	0.0804
LOC_{ij}	-0.0079	0.0016	-0.0109	-0.0048	ALI_{ijt}	0.0057	0.0014	0.0031	0.0083
ISL_{ij}	0.0064	0.0022	0.0019	0.0106	HOS_{ij}	-0.0332	0.0047	-0.0426	-0.0243
LAN_{ij}	0.0228	0.0021	0.0187	0.0269	ρ	0.6532	0.0015	0.6503	0.6562
REL_{ij}	0.0074	0.0011	0.0054	0.0096					
COL_{ij}	0.0614	0.0085	0.0460	0.0787					
COZ_{ij}	0.0418	0.0075	0.0271	0.0566					
$CCOL_{ij}$	0.0294	0.0068	0.0165	0.0428					
$CCOZ_{ij}$	0.0728	0.0085	0.0567	0.0900					
MH Acc Rate	34.68%								
MSEP	11.8203								
Num of Iters	30,000(Burn-in rate 50%)								

Note: Hyperparameters: N_τ=N_ε=N_c=N_d=N_e=1, R_τ=R_ε=R_c=R_d=R_e=1; Tuning parameter: σ_τ^2=0.0001

Lower bound and upper bound of 95% credible intervals for the parameters

Estimation results are from estimation using data from 1948 to 2001.

Data for 2002 used for out-of-sample model selection.

Table 1.7: Posterior Distributions of Coefficients

	Coefficient		Credible Interval			Coefficient		Credible Interval	
	Mean	Std.Dev.	Lower	Upper		Mean	Std.Dev	Lower	Upper
log GDP_{it}	0.7996	0.0136	0.7742	0.8272	COM_{ij}	0.6170	0.0321	0.5522	0.6797
log GDP_{jt}	0.6517	0.0135	0.6262	0.6767	REM_{ijt}	-0.0382	0.0064	-0.0514	-0.0261
log $PerGDP_{it}$	0.2797	0.0188	0.2446	0.3152	$BOTH_{ijt}$	0.1795	0.0824	0.0213	0.3163
log $PerGDP_{jt}$	0.3214	0.0209	0.2811	0.3621	ONE_{ijt}	0.0744	0.0421	-0.0074	0.1471
log $Dist_{ij}$	-1.1329	0.0172	-1.1685	-1.0009	RTA_{ijt}	0.2395	0.0099	0.2203	0.2589
log $Area_i$	-0.0795	0.0085	-0.0959	-0.0641	$EIGSP_{ijt}$	-0.0608	0.0139	-0.0873	-0.0333
log $Area_j$	-0.0885	0.0103	-0.1083	-0.0686	$IEGSP_{ijt}$	-0.0163	0.0147	-0.0465	0.0116
BOR_{ij}	0.7905	0.0646	0.6634	0.9137	CU_{ijt}	0.9594	0.0299	0.8998	1.0163
LOC_{ij}	-0.1694	0.0276	-0.2239	-0.1149	ALI_{ijt}	0.1639	0.0145	0.1363	0.1929
ISL_{ij}	0.2692	0.0321	0.2119	0.3337	HOS_{ij}	-0.5133	0.0876	-0.6865	-0.3444
LAN_{ij}	0.3423	0.0363	0.2717	0.4175	ρ	-	-	-	-
REL_{ij}	0.0849	0.0199	0.0455	0.1213	τ	0.0002	1.3×10^{-6}	0.0002	0.0002
COL_{ij}	1.5730	0.1183	1.3400	1.8208	σ^2_ε	1.5351	0.0047	1.5257	1.5439
COZ_{ij}	1.1689	0.1197	0.9387	1.4117	σ^2_α	1.7729	0.0176	1.7391	1.8081
$CCOL_{ij}$	-0.2189	0.0569	-0.3311	-0.1087	σ^2_ζ	0.7617	0.0176	0.7267	0.7953
$CCOZ_{ij}$	0.2828	0.0559	0.1688	0.3871	σ^2_ν	1.2610	0.0266	1.2076	1.3120
MH Acc Rate	26.86%								
MSEP	596.8190								
Num of Iters	30,000(Burn-in rate 50%)								

Note: Hyperparameters: N_τ=N_ε=N_c=N_d=N_e=1, R_τ=R_ε=R_c=R_d=R_e=1; Tuning parameter: σ^2_τ=0.0001

Lower bound and upper bound of 95% credible intervals for the parameters

Estimation results are from estimation using data from 1948 to 2001.

Data for 2002 used for out-of-sample model selection.

Table 1.8: Posterior Distributions of Marginal Effects

	Marginal Effects		Credible Interval			Marginal Effects		Credible Interval	
	Mean	Std.Dev.	Lower	Upper		Mean	Std.Dev	Lower	Upper
log GDP_{it}	0.1872	0.0041	0.1791	0.1952	COM_{ij}	0.1886	0.0131	0.1630	0.2145
log GDP_{jt}	0.1525	0.0038	0.1451	0.1599	REM_{ijt}	-0.0090	0.0015	-0.0120	-0.0060
log $PerGDP_{it}$	0.0655	0.0045	0.0570	0.0742	$BOTH_{ijt}$	0.0389	0.0170	0.0057	0.0669
log $PerGDP_{jt}$	0.0752	0.0050	0.0653	0.0848	ONE_{ijt}	0.0151	0.0081	-0.0006	0.0290
log $Dist_{ij}$	-0.2652	0.0056	-0.2760	-0.2544	RTA_{ijt}	0.0593	0.0028	0.0539	0.0647
log $Area_i$	-0.0186	0.0020	-0.0226	-0.0150	$EIGSP_{ijt}$	-0.0139	0.0031	-0.0199	-0.0077
log $Area_j$	-0.0207	0.0024	-0.0254	-0.0159	$IEGSP_{ijt}$	-0.0038	0.0034	-0.0105	0.0029
BOR_{ij}	0.2494	0.0280	0.1953	0.3038	CU_{ijt}	0.3719	0.0187	0.3350	0.4075
LOC_{ij}	-0.0370	0.0057	-0.0478	-0.0255	ALI_{ijt}	0.0389	0.0036	0.0319	0.0458
ISL_{ij}	0.0666	0.0085	0.0512	0.0836	HOS_{ij}	-0.1201	0.0205	-0.1602	-0.0802
LAN_{ij}	0.0906	0.0109	0.0692	0.1131	ρ	-	-	-	-
REL_{ij}	0.0196	0.0045	0.0106	0.0280					
COL_{ij}	0.8638	0.1283	0.6011	1.1146					
COZ_{ij}	0.5086	0.0879	0.3503	0.6977					
$CCOL_{ij}$	-0.0457	0.0107	-0.0659	-0.0238					
$CCOZ_{ij}$	0.0770	0.0174	0.0418	0.1095					
MH Acc Rate	26.86%								
MSEP	596.8190								
Num of Iters	30,000(Burn-in rate 50%)								

Note: Hyperparameters: N_τ=N_ε=N_c=N_d=N_e=1, R_τ=R_ε=R_c=R_d=R_e=1; Tuning parameter: σ_τ^2=0.0001

Lower bound and upper bound of 95% credible intervals for the parameters

Estimation results are from estimation using data from 1948 to 2001.

Data for 2002 used for out-of-sample model selection.

Table 1.9: Geweke's Diagnostic of Coefficients

	Z score	P value		Z score	P value
log GDP_{it}	-2.1012	0.0356	COM_{ij}	0.4397	0.6602
log GDP_{jt}	0.4643	0.6424	REM_{ijt}	-0.4368	0.6623
log $PerGDP_{it}$	0.9513	0.3415	$BOTH_{ijt}$	-2.2850	0.0223
log $PerGDP_{jt}$	-0.7924	0.4281	ONE_{ijt}	-2.3310	0.0198
log $Dist_{ij}$	-0.3035	0.7615	RTA_{ijt}	0.1982	0.8429
log $Area_{i}$	0.8221	0.4110	$EIGSP_{ijt}$	1.9416	0.0522
log $Area_{j}$	-1.3719	0.1701	$IEGSP_{ijt}$	-1.1129	0.2657
BOR_{ij}	-0.6263	0.5311	CU_{ijt}	-1.3510	0.1767
LOC_{ij}	-1.6918	0.0907	ALI_{ijt}	-0.4938	0.6215
ISL_{ij}	0.8597	0.3900	HOS_{ij}	-0.5341	0.5933
LAN_{ij}	0.5001	0.6170	ρ	-0.8620	0.3887
REL_{ij}	0.0133	0.9894	τ	1.5104	0.1310
COL_{ij}	0.5277	0.5977	σ_{ε}^2	-1.4783	0.1393
COZ_{ij}	-2.0045	0.0450	σ_{α}^2	-1.3863	0.1656
$CCOL_{ij}$	0.4720	0.6369	σ_{ζ}^2	-0.1772	0.8594
$CCOZ_{ij}$	0.0536	0.9573	σ_{ν}^2	0.3613	0.7179

Note: Geweke (1992) develops a convergence diagnostic for the Markov chain based on a test for equality of means of the first 10% and the last 50% of the chain. The test statistic is a standard Z score with the standard errors adjusted for autocorrelation. The large absolute value of Geweke's statistic indicates that the chain has not converged.

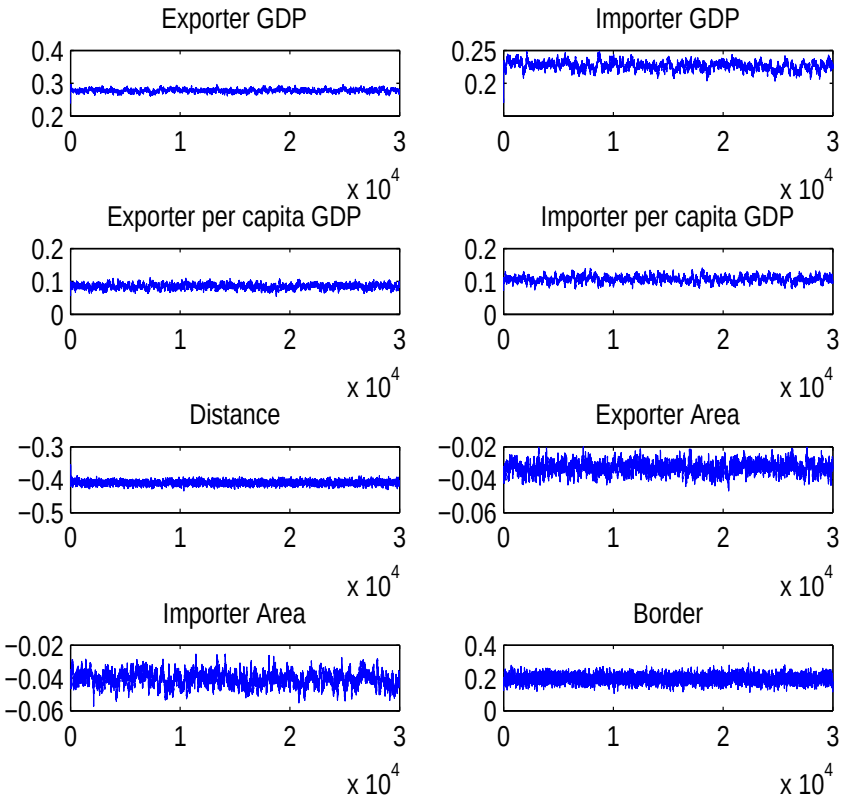

Figure 1.1: Trace Plot 1

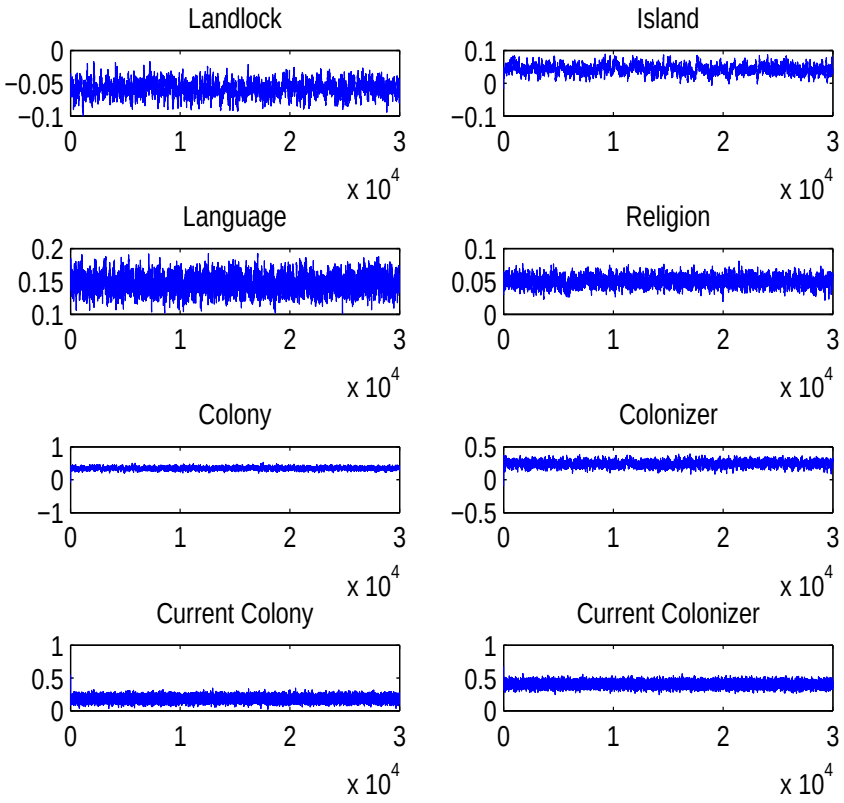

Figure 1.2: Trace Plot 2

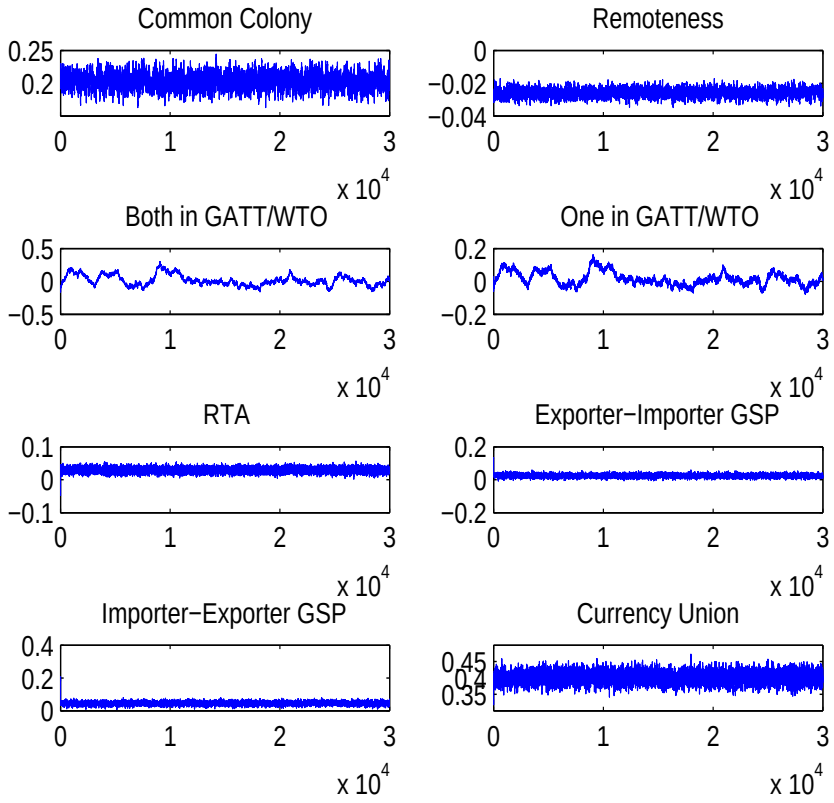

Figure 1.3: Trace Plot 3

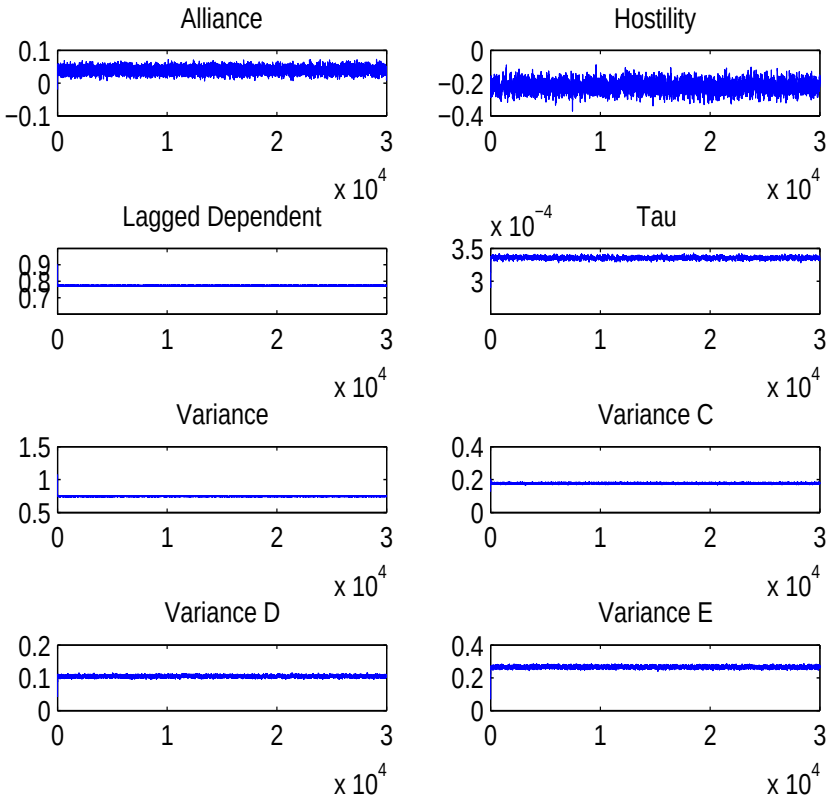

Figure 1.4: Trace Plot 4 (Variance, Variance C, Variance D and Variance E correspond to $\sigma^2_\varepsilon, \sigma^2_\alpha, \sigma^2_\zeta$ and σ^2_v)

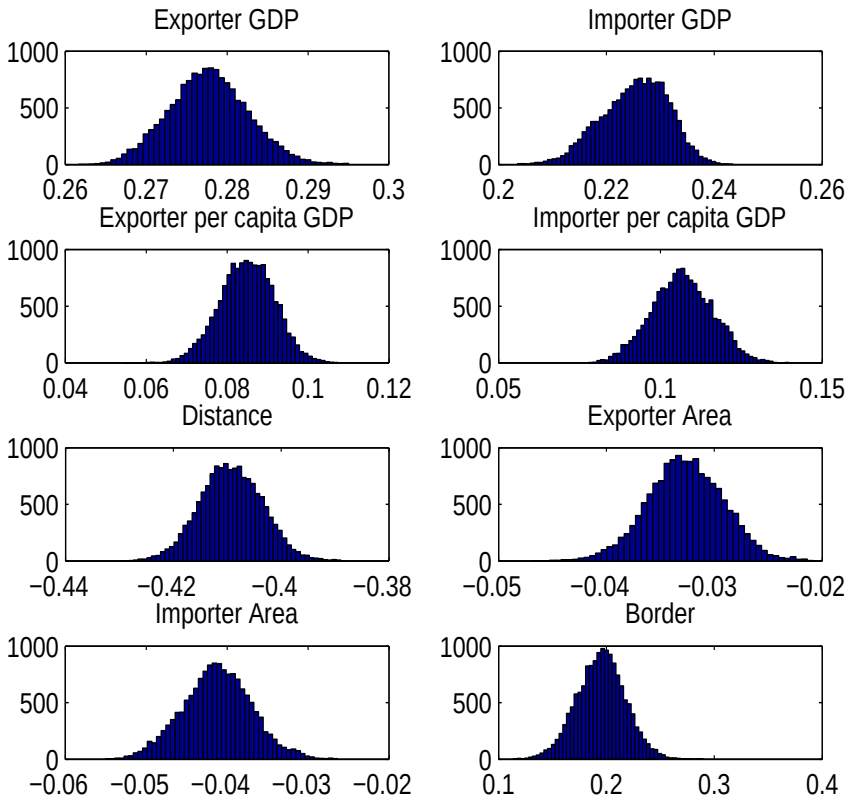

Figure 1.5: Posterior Distributions of Coefficients 1 (These are based on the last 15,000 iterations)

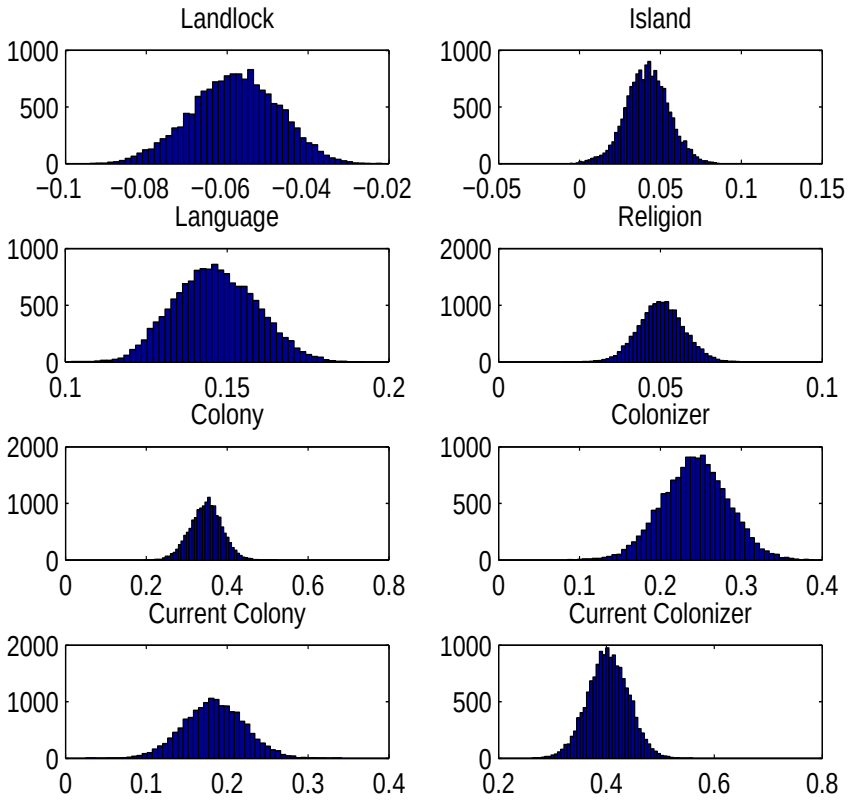

Figure 1.6: Posterior Distributions of Coefficients 2

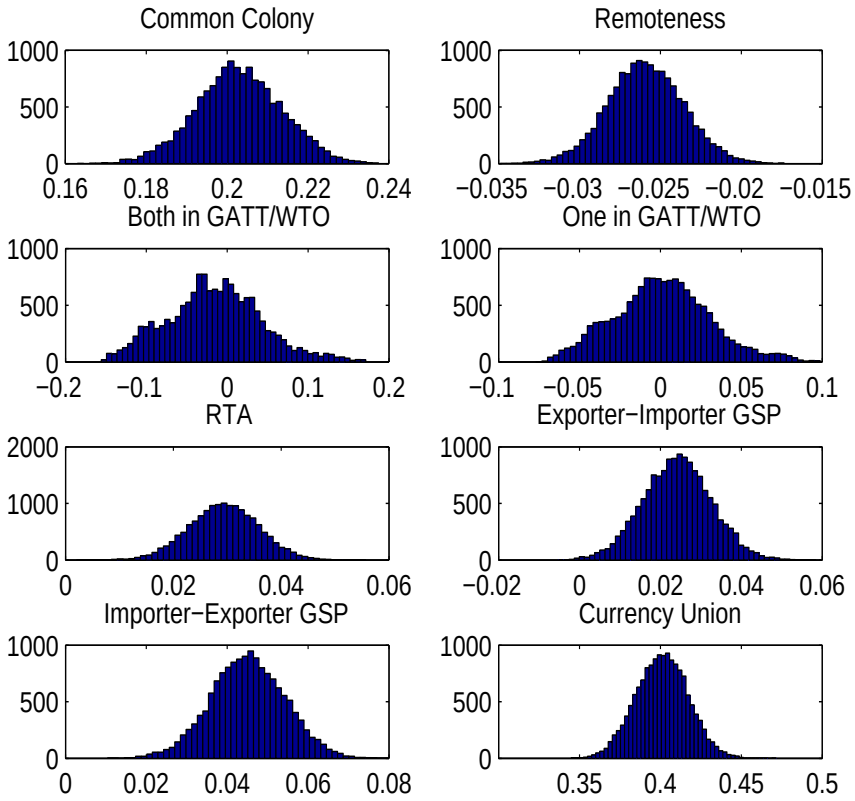

Figure 1.7: Posterior Distributions of Coefficients 3

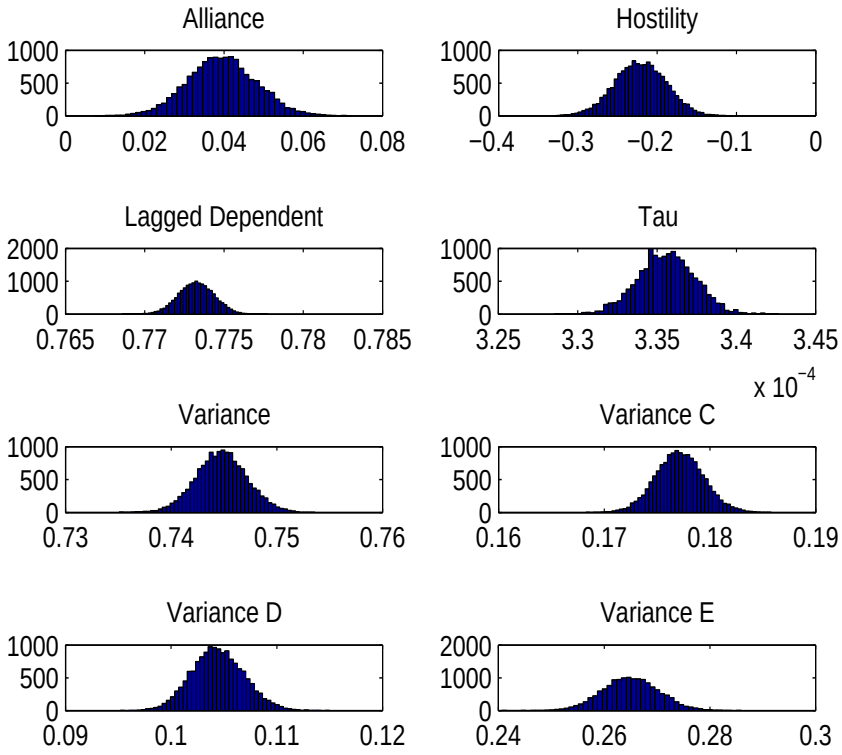

Figure 1.8: Posterior Distributions of Coefficients 4 (Variance, Variance C, Variance D and Variance E correspond to $\sigma_\varepsilon^2, \sigma_\alpha^2, \sigma_\zeta^2$ and σ_v^2)

Chapter 2

Robust Estimation of Dynamic Panel Data Gravity Model with Multiple Sets of Unobserved Effects

2.1 Introduction

Since the seminal work by Santos Silva and Tenreyro (2006), the Poisson pseudo maximum likelihood (PPML) estimator has become the new workhorse for estimating gravity models in the trade literature. The PPML estimator is attractive mainly for three reasons. First, observations with zero trade volume can be included in the estimation, avoiding sample selection bias. Second, it is robust because only the conditional mean assumption for the dependent variable is required for consistency. More specifically, the estimation is robust to heteroskedasticity, which is believed to be a prevalent feature of trade data. Third, it can be easily implemented as canned statistical software like Stata has commands available to carry out the estimation.

To date, the application of the PPML estimator to gravity models has been limited to static gravity models with at most one set of unobserved effects, probably due to the fact that only such models can be readily estimated by canned statistical software like Stata. For example, Liu (2009) examines the effects of GATT/WTO membership on trade by estimating a static gravity model with time-invariant country-pair unobserved effects. However, the recent literature shows that such a gravity model misses many important determinants of trade volume. First, Wei (1996), Deardorff (1998), Anderson and van Wincoop (2003) and Anderson (2011) emphasize that "multilateral resistance" is an important determinant of trade volume and Anderson and van Wincoop (2003) suggest that this term can be taken into account in the gravity model through unobserved time-varying country-specific effects, as in Subramanian and Wei (2007). This implies that in addition to the time-invariant country-pair unobserved effects,

two other sets of unobserved effects should be included: the time-varying importer unobserved effects and the time-varying exporter unobserved effects. Second, both Roberts and Tybout (1997) and Bernard and Jensen (2004) find that sunk entry and exit costs play an important role in firms' export behavior and firms that exported in previous periods are more likely to export in the current period. Clerides, Lach and Tybout (1998) find evidence of positive regional externalities on exports, that is, the presence of other exporters in the same region makes producers more likely to enter foreign markets. If trade volume in previous periods is an important determinant of trade volume in the current period at the micro level, then the same pattern should be observed at the aggregate level as well, because aggregate data are simply the summation of micro level data. This implies that the trade volume in previous periods or the lagged dependent variables should be included as one of the main determinants in gravity model estimation. Without these important determinants, the estimates may be biased due to the omitted variable problem.

In this chapter, I intend to propose a method for estimating the dynamic gravity model with multiple sets of unobserved effects with minimal assumptions. Unlike the method proposed in Chapter 1 and similar to the PPML, the estimator here will only rely on the conditional mean assumption for the dependent variable. I will then apply the estimator to study the persistence of trade flows and the effect of a regional trade agreement (RTA) on trade.

2.2 The Moment Condition

Let Y_{ijt} denote exports from country i to country j ($i \neq j$) in year t. I assume Y_{ijt} is determined by the following model,

$$Y_{ijt} = d_{it} * e_{jt} * c_{ij} * \exp(z_{ijt}\gamma) * \varepsilon_{ijt}. \tag{2.1}$$

In (2.1), d_{it} and e_{jt} are the time-varying exporter and importer specific unobserved effects, respectively, to control for each country's "multilateral resistance" and c_{ij} is the time-invariant country-pair specific unobserved effects. z_{ijt} is a set of observed trade barrier or facilitation variables, and ε_{ijt} is an i.i.d. error term. It is worth noting that d_{it}, e_{jt} and c_{ij} are all assumed to be fixed effects so that they are allowed to be arbitrarily correlated with covariates z_{ijt}.

2.2.1 The Strictly Exogenous Case

I first study the case where the covariates in (2.1) are strictly exogenous. This rules out the case with lagged dependent variables. More specifically, the assumption here is that

$$E[\varepsilon_{ijt}|\lambda, \mathbf{d}, \mathbf{e}, \mathbf{c}] = 1 \ \forall \ ijt, \tag{2.2}$$

where $\lambda_{ijt} = \exp(z_{ijt}\gamma)$, λ collects $\lambda_{ijt}\ \forall\ ijt$ and $\mathbf{d}$, $\mathbf{e}$ and $\mathbf{c}$ are similarly defined. This assumption is equivalent to

$$E[Y_{ijt}|\lambda, \mathbf{d}, \mathbf{e}, \mathbf{c}] = E[Y_{ijt}|\lambda_{ijt}, d_{it}, e_{jt}, c_{ij}] = d_{it} * e_{jt} * c_{ij} * \exp(z_{ijt}\gamma).$$

With this assumption, I have[1]

$$\begin{aligned}
& E[Y_{ijt}Y_{lkt}Y_{ikt+1}Y_{ljt+1}\lambda_{ikt}\lambda_{ljt}\lambda_{ijt+1}\lambda_{lkt+1}|\lambda, \mathbf{d}, \mathbf{e}, \mathbf{c}] \\
= \ & d_{it}e_{jt}c_{ij}\lambda_{ijt}d_{lt}e_{kt}c_{lk}\lambda_{lkt}d_{it+1}e_{kt+1}c_{ik}\lambda_{ikt+1}d_{lt+1}e_{jt+1}c_{lj}\lambda_{ljt+1}\lambda_{ikt}\lambda_{ljt}\lambda_{ijt+1}\lambda_{lkt+1} \\
& * E[\varepsilon_{ijt}\varepsilon_{lkt}\varepsilon_{ikt+1}\varepsilon_{ljt+1}|\lambda, \mathbf{d}, \mathbf{e}, \mathbf{c}] \\
= \ & d_{it}e_{jt}c_{ij}\lambda_{ijt}d_{lt}e_{kt}c_{lk}\lambda_{lkt}d_{it+1}e_{kt+1}c_{ik}\lambda_{ikt+1}d_{lt+1}e_{jt+1}c_{lj}\lambda_{ljt+1}\lambda_{ikt}\lambda_{ljt}\lambda_{ijt+1}\lambda_{lkt+1} \\
& * E[\varepsilon_{ijt}|\lambda, \mathbf{d}, \mathbf{e}, \mathbf{c}]\, E[\varepsilon_{lkt}|\lambda, \mathbf{d}, \mathbf{e}, \mathbf{c}]\, E[\varepsilon_{ikt+1}|\lambda, \mathbf{d}, \mathbf{e}, \mathbf{c}]\, E[\varepsilon_{ljt+1}|\lambda, \mathbf{d}, \mathbf{e}, \mathbf{c}] \\
= \ & d_{it}e_{jt}c_{ij}\lambda_{ijt}d_{lt}e_{kt}c_{lk}\lambda_{lkt}d_{it+1}e_{kt+1}c_{ik}\lambda_{ikt+1}d_{lt+1}e_{jt+1}c_{lj}\lambda_{ljt+1}\lambda_{ikt}\lambda_{ljt}\lambda_{ijt+1}\lambda_{lkt+1}. \quad (2.3)
\end{aligned}$$

Similarly, it can be shown that

$$\begin{aligned}
& E[Y_{ikt}Y_{ljt}Y_{ijt+1}Y_{lkt+1}\lambda_{ijt}\lambda_{lkt}\lambda_{ikt+1}\lambda_{ljt+1}|\lambda, \mathbf{d}, \mathbf{e}, \mathbf{c}] \\
= \ & d_{it}e_{kt}c_{ik}\lambda_{ikt}d_{lt}e_{jt}c_{lj}\lambda_{ljt}d_{it+1}e_{jt+1}c_{ij}\lambda_{ijt+1}d_{lt+1}e_{kt+1}c_{lk}\lambda_{lkt+1}\lambda_{ijt}\lambda_{lkt}\lambda_{ikt+1}\lambda_{ljt+1}. \quad (2.4)
\end{aligned}$$

(2.3) and (2.4) then imply that

$$E[Y_{ijt}Y_{lkt}Y_{ikt+1}Y_{ljt+1}\lambda_{ikt}\lambda_{ljt}\lambda_{ijt+1}\lambda_{lkt+1} - Y_{ijt}Y_{lkt}Y_{ikt+1}Y_{ljt+1}\lambda_{ikt}\lambda_{ljt}\lambda_{ijt+1}\lambda_{lkt+1}|\lambda, \mathbf{d}, \mathbf{e}, \mathbf{c}] = 0,$$

which further implies

$$E[Y_{ijt}Y_{lkt}Y_{ikt+1}Y_{ljt+1}\lambda_{ikt}\lambda_{ljt}\lambda_{ijt+1}\lambda_{lkt+1} - Y_{ijt}Y_{lkt}Y_{ikt+1}Y_{ljt+1}\lambda_{ikt}\lambda_{ljt}\lambda_{ijt+1}\lambda_{lkt+1}|\lambda] = 0 \quad (2.5)$$

by law of iterated expectations. (2.5) then can be used as the basis to form moment conditions in the GMM estimation of γ, the parameter vector of interest. For the case where the covariates are strictly exogenous, Cameron and Trivedi (1998, Section 9.3.3) derive the moment condition for a model similar to (2.1) but with just one set of fixed effects, while Charbonneau (2012) derives the moment condition for a model similar to (2.1) but with two sets of fixed effects.

2.2.2 The Sequentially Exogenous Case

The strict exogeneity assumption (2.2) is restrictive in the sense that certain models of economic interest are ruled out. One case in which strict exogeneity cannot hold is when a lagged

[1] Note that $i \neq j$ and for the same reason, $l \neq k$.

dependent variable is included in z_{ijt}. It also rules out the possibility of any feedback from Y_{ijt} to future z_{ijt}. A weaker assumption that allows both cases is the following sequential exogeneity assumption,

$$E\left[\varepsilon_{ijt}|\lambda_1,...,\lambda_{\mathbf{t}},\mathbf{d},\mathbf{e},\mathbf{c}\right]=1\ \forall\ ijt. \tag{2.6}$$

In addition, I also assume that

$$Cov\left[\varepsilon_{ijt},\varepsilon_{lkt'}|\lambda_1,...,\lambda_{\mathbf{t}},\mathbf{d},\mathbf{e},\mathbf{c}\right]=0\ \forall\ i\neq l \text{ or } j\neq k \text{ and } \forall\ t'\geq t, \tag{2.7}$$

where $\lambda_{\mathbf{t}}$ collects $\lambda_{ijt}\ \forall\ ij$ and other variables are similarly defined. Chamberlain (1992), Blundell, Griffith and Windmeijer (1995) and Wooldridge (1997) have proposed robust estimators that can be used to estimate the model (2.1) under (2.6) with just one set of unobserved effects. Here, I extend their methods to the case with multiple sets of unobserved effects.

The assumption of (2.6) with (2.1) is equivalent to

$$E\left[Y_{ijt}|\lambda_1,...,\lambda_{\mathbf{t}},\mathbf{d},\mathbf{e},\mathbf{c}\right]=E\left[Y_{ijt}|\lambda_{ijt},d_{it},e_{jt},c_{ij}\right]=d_{it}*e_{jt}*c_{ij}*\exp\left(z_{ijt}\gamma\right).$$

With this, I have[2]

$$\begin{aligned}
& E\left[Y_{ijt}Y_{lkt}Y_{ikt+1}Y_{ljt+1}\frac{\lambda_{ikt}\lambda_{ljt}}{\lambda_{ikt+1}\lambda_{ljt+1}}\middle|\lambda_1,...,\lambda_{\mathbf{t}},\mathbf{d},\mathbf{e},\mathbf{c}\right] \\
= & d_{it}e_{jt}c_{ij}\lambda_{ijt}d_{lt}e_{kt}c_{lk}\lambda_{lkt}\lambda_{ikt}\lambda_{ljt}E\left[\frac{\varepsilon_{ijt}\varepsilon_{lkt}Y_{ikt+1}Y_{ljt+1}}{\lambda_{ikt+1}\lambda_{ljt+1}}\middle|\lambda_1,...,\lambda_{\mathbf{t}},\mathbf{d},\mathbf{e},\mathbf{c}\right] \\
= & d_{it}e_{jt}c_{ij}\lambda_{ijt}d_{lt}e_{kt}c_{lk}\lambda_{lkt}\lambda_{ikt}\lambda_{ljt} \\
& *d_{it+1}e_{kt+1}c_{ik}d_{lt+1}e_{jt+1}c_{lj}E\left[\frac{\varepsilon_{ijt}\varepsilon_{lkt}\lambda_{ikt+1}\varepsilon_{ikt+1}\lambda_{ljt+1}\varepsilon_{ljt+1}}{\lambda_{ikt+1}\lambda_{ljt+1}}\middle|\lambda_1,...,\lambda_{\mathbf{t}},\mathbf{d},\mathbf{e},\mathbf{c}\right] \\
= & d_{it}e_{jt}c_{ij}\lambda_{ijt}d_{lt}e_{kt}c_{lk}\lambda_{lkt}\lambda_{ikt}\lambda_{ljt} \\
& *d_{it+1}e_{kt+1}c_{ik}d_{lt+1}e_{jt+1}c_{lj}E\left[\varepsilon_{ijt}\varepsilon_{lkt}\varepsilon_{ikt+1}\varepsilon_{ljt+1}|\,\lambda_1,...,\lambda_{\mathbf{t}},\mathbf{d},\mathbf{e},\mathbf{c}\right] \\
= & d_{it}e_{jt}c_{ij}\lambda_{ijt}d_{lt}e_{kt}c_{lk}\lambda_{lkt}\lambda_{ikt}\lambda_{ljt}d_{it+1}e_{kt+1}c_{ik}d_{lt+1}e_{jt+1}c_{lj} \\
& *E\left[\varepsilon_{ijt}|\,\lambda_1,...,\lambda_{\mathbf{t}},\mathbf{d},\mathbf{e},\mathbf{c}\right]E\left[\varepsilon_{lkt}|\,\lambda_1,...,\lambda_{\mathbf{t}},\mathbf{d},\mathbf{e},\mathbf{c}\right] \\
& *E\left[\varepsilon_{ikt+1}|\,\lambda_1,...,\lambda_{\mathbf{t}},\mathbf{d},\mathbf{e},\mathbf{c}\right]E\left[\varepsilon_{ljt+1}|\,\lambda_1,...,\lambda_{\mathbf{t}},\mathbf{d},\mathbf{e},\mathbf{c}\right] \\
= & d_{it}e_{jt}c_{ij}\lambda_{ijt}d_{lt}e_{kt}c_{lk}\lambda_{lkt}\lambda_{ikt}\lambda_{ljt}d_{it+1}e_{kt+1}c_{ik}d_{lt+1}e_{jt+1}c_{lj} \\
& *E\left[\varepsilon_{ikt+1}|\,\lambda_1,...,\lambda_{\mathbf{t}},\mathbf{d},\mathbf{e},\mathbf{c}\right]E\left[\varepsilon_{ljt+1}|\,\lambda_1,...,\lambda_{\mathbf{t}},\mathbf{d},\mathbf{e},\mathbf{c}\right] \\
= & d_{it}e_{jt}c_{ij}\lambda_{ijt}d_{lt}e_{kt}c_{lk}\lambda_{lkt}\lambda_{ikt}\lambda_{ljt}d_{it+1}e_{kt+1}c_{ik}d_{lt+1}e_{jt+1}c_{lj} \\
& *E\left[E\left[\varepsilon_{ikt+1}|\,\lambda_1,...,\lambda_{\mathbf{t+1}},\mathbf{d},\mathbf{e},\mathbf{c}\right]\right]E\left[E\left[\varepsilon_{ljt+1}|\,\lambda_1,...,\lambda_{\mathbf{t+1}},\mathbf{d},\mathbf{e},\mathbf{c}\right]\right] \\
= & d_{it}d_{lt}d_{it+1}d_{lt+1}e_{jt}e_{kt}e_{jt+1}e_{kt+1}c_{ij}c_{ik}c_{lj}c_{lk}\lambda_{ijt}\lambda_{ikt}\lambda_{ljt}\lambda_{lkt},
\end{aligned} \tag{2.8}$$

[2]Note that $i\neq j$ and for the same reason, $l\neq k$.

where the fourth equality follows from (2.7) and the sixth equality follows from the law of iterated expectations. Similarly, it can be shown that

$$\begin{aligned} & E\left[Y_{ikt}Y_{ljt}Y_{ijt+1}Y_{lkt+1}\frac{\lambda_{ijt}\lambda_{lkt}}{\lambda_{ijt+1}\lambda_{lkt+1}}\middle|\lambda_1,...,\lambda_{\mathbf{t}},\mathbf{d},\mathbf{e},\mathbf{c}\right] \\ = \; & d_{it}d_{lt}d_{it+1}d_{lt+1}e_{jt}e_{kt}e_{jt+1}e_{kt+1}c_{ij}c_{ik}c_{lj}c_{lk}\lambda_{ijt}\lambda_{ikt}\lambda_{ljt}\lambda_{lkt}. \end{aligned} \tag{2.9}$$

(2.8) and (2.9) together imply that

$$E\left[Y_{ijt}Y_{lkt}Y_{ikt+1}Y_{ljt+1}\frac{\lambda_{ikt}\lambda_{ljt}}{\lambda_{ikt+1}\lambda_{ljt+1}}-Y_{ikt}Y_{ljt}Y_{ijt+1}Y_{lkt+1}\frac{\lambda_{ijt}\lambda_{lkt}}{\lambda_{ijt+1}\lambda_{lkt+1}}\middle|\lambda_1,...,\lambda_{\mathbf{t}},\mathbf{d},\mathbf{e},\mathbf{c}\right]=0,$$

which further implies

$$E\left[Y_{ijt}Y_{lkt}Y_{ikt+1}Y_{ljt+1}\frac{\lambda_{ikt}\lambda_{ljt}}{\lambda_{ikt+1}\lambda_{ljt+1}}-Y_{ikt}Y_{ljt}Y_{ijt+1}Y_{lkt+1}\frac{\lambda_{ijt}\lambda_{lkt}}{\lambda_{ijt+1}\lambda_{lkt+1}}\middle|\lambda_1,...,\lambda_{\mathbf{t}}\right]=0. \tag{2.10}$$

(2.10) can be used as the basis to form moment conditions in the GMM estimation of γ, the parameter vector of interest.

2.3 GMM Estimation

Rewrite (2.10) as

$$E\left[q_{ij,lk,t}|\,\lambda_1,...,\lambda_{\mathbf{t}}\right]=0, \tag{2.11}$$

where $q_{ij,lk,t}=Y_{ijt}Y_{lkt}Y_{ikt+1}Y_{ljt+1}\frac{\lambda_{ikt}\lambda_{ljt}}{\lambda_{ikt+1}\lambda_{ljt+1}}-Y_{ikt}Y_{ljt}Y_{ijt+1}Y_{lkt+1}\frac{\lambda_{ijt}\lambda_{lkt}}{\lambda_{ijt+1}\lambda_{lkt+1}}$. As a result, I can interact $q_{ij,lk,t}$ with any variables or functions of variables in $\lambda_1,...,\lambda_t$ to form the moment conditions for GMM estimation. For example, when z_{ijt} is used, the two-step optimal GMM estimator $\widehat{\gamma}_{GMM}^{2step}$ is the solution to the following minimization problem

$$\left(\sum_{i=1}^{I}\sum_{j\neq i}^{J_i}\sum_{t=t_{ij}^0}^{t_{ij}^1-1}\sum_{l\neq i \text{ or } k(\neq l)\neq j} z'_{ijt}*q_{ij,lk,t}\right)'\widetilde{S}^{-1}\left(\sum_{i=1}^{I}\sum_{j\neq i}^{J_i}\sum_{t=t_{ij}^0}^{t_{ij}^1-1}\sum_{l\neq i \text{ or } k(\neq l)\neq j} z'_{ijt}*q_{ij,lk,t}\right), \tag{2.12}$$

where I (J_i) is the number of exporters (importers),[3] t_{ij}^0 and t_{ij}^1 are the second and last time periods where I have data for country pair ij,[4][5] $\widetilde{S}=\frac{1}{N}\sum_{i=1}^{I}\sum_{j\neq i}^{J_i}\sum_{t=t_{ij}^0}^{t_{ij}^1-1}\sum_{l\neq i \text{ or } k(\neq l)\neq j}\widetilde{u}_{ij,lk,t}^2 z'_{ijt}z_{ijt}$,

[3]Note that the numbers of importers for different exporters are different. Thus, the number of importer for each exporter i is J_i rather than J.

[4]Note that if $i=l$ or $j=k$, $q_{ij,lk,t}$ is identically zero. For example, if $i=l$ and $j\neq k$, $q_{ij,lk,t}=q_{ij,ik,t}=Y_{ijt}Y_{ikt}Y_{ikt+1}Y_{ijt+1}\frac{\lambda_{ikt}\lambda_{ijt}}{\lambda_{ikt+1}\lambda_{ijt+1}}-Y_{ikt}Y_{ijt}Y_{ijt+1}Y_{ikt+1}\frac{\lambda_{ijt}\lambda_{ikt}}{\lambda_{ijt+1}\lambda_{ikt+1}}=0$.

[5]The first period is used for the initial condition.

$\widetilde{u}_{ij,lk,t} = Y_{ijt}Y_{lkt}Y_{ikt+1}Y_{ljt+1}\frac{\exp(z_{ikt}\widetilde{\gamma})\exp(z_{ljt}\widetilde{\gamma})}{\exp(z_{ikt+1}\widetilde{\gamma})\exp(z_{ljt+1}\widetilde{\gamma})} - Y_{ikt}Y_{ljt}Y_{ijt+1}Y_{lkt+1}\frac{\exp(z_{ijt}\widetilde{\gamma})\exp(z_{lkt}\widetilde{\gamma})}{\exp(z_{ijt+1}\widetilde{\gamma})\exp(z_{lkt+1}\widetilde{\gamma})}$ and $\widetilde{\gamma}$ is the solution to the following minimization problem in the first step,

$$\left(\sum_{i=1}^{I}\sum_{j\neq i}^{J_i}\sum_{t=t_{ij}^0}^{t_{ij}^1-1}\sum_{l\neq i \text{ or } k(\neq l)\neq j} z'_{ijt} * q_{ij,lk,t}\right)' I_\kappa \left(\sum_{i=1}^{I}\sum_{j\neq i}^{J_i}\sum_{t=t_{ij}^0}^{t_{ij}^1-1}\sum_{l\neq i \text{ or } k(\neq l)\neq j} z'_{ijt} * q_{ij,lk,t}\right). \quad (2.13)$$

In (2.13), I_κ is the $\kappa \times \kappa$ identity matrix, where κ is the number of variables in z_{ijt}.

To conduct statistical inference, the variance-covariance matrix of $\widehat{\gamma}_{GMM}^{2step}$ also needs to be computed. For the two-step optimal GMM estimator, the variance-covariance matrix can be computed using $\widehat{Var}\left[\widehat{\gamma}_{GMM}^{2step}\right] = \frac{\left(\widehat{H}'\widehat{S}^{-1}\widehat{H}\right)^{-1}}{N}$, where

$$\begin{aligned}
\widehat{H} &= \frac{1}{N}\sum_{i=1}^{I}\sum_{j\neq i}^{J_i}\sum_{t=t_{ij}^0}^{t_{ij}^1-1}\sum_{l\neq i \text{ or } k(\neq l)\neq j} \left.\frac{\partial z'_{ijt} * q_{ij,lk,t}}{\partial \gamma'}\right|_{\widehat{\gamma}_{GMM}^{2step}} \\
&= \frac{1}{N}\sum_{i=1}^{I}\sum_{j\neq i}^{J_i}\sum_{t=t_{ij}^0}^{t_{ij}^1-1}\sum_{l\neq i \text{ or } k(\neq l)\neq j} z'_{ijt} * \left\{ \begin{array}{l} \left[\begin{array}{c} Y_{ijt}Y_{lkt}Y_{ikt+1}Y_{ljt+1} \\ \frac{\exp\left(z_{ikt}\widehat{\gamma}_{GMM}^{2step}\right)\exp\left(z_{ljt}\widehat{\gamma}_{GMM}^{2step}\right)}{\exp\left(z_{ikt+1}\widehat{\gamma}_{GMM}^{2step}\right)\exp\left(z_{ljt+1}\widehat{\gamma}_{GMM}^{2step}\right)} \\ * \left(z_{ikt} + z_{ljt} - z_{ikt+1} - z_{ljt+1}\right) \end{array} \right] \\ - \left[\begin{array}{c} Y_{ikt}Y_{ljt}Y_{ijt+1}Y_{lkt+1} \\ \frac{\exp\left(z_{ijt}\widehat{\gamma}_{GMM}^{2step}\right)\exp\left(z_{lkt}\widehat{\gamma}_{GMM}^{2step}\right)}{\exp\left(z_{ijt+1}\widehat{\gamma}_{GMM}^{2step}\right)\exp\left(z_{lkt+1}\widehat{\gamma}_{GMM}^{2step}\right)} \\ * \left(z_{ijt} + z_{lkt} - z_{ijt+1} - z_{lkt+1}\right) \end{array} \right] \end{array} \right\},
\end{aligned}$$

$N = \sum_{i=1}^{I}\sum_{j=i}^{J_i}\sum_{t=t_{ij}^0}^{t_{ij}^1-1}\sum_{l\neq i \text{ or } k(\neq l)\neq j} 1$ is the total number of observations in the sample,

$$\widehat{S} = \frac{1}{N}\sum_{i=1}^{I}\sum_{j\neq i}^{J_i}\sum_{t=t_{ij}^0}^{t_{ij}^1-1}\sum_{l\neq i \text{ or } k(\neq l)\neq j} \widehat{u}_{ij,lk,t}^2 z'_{ijt}z_{ijt},$$

and

$$\begin{aligned}
\widehat{u}_{ij,lk,t} &= Y_{ijt}Y_{lkt}Y_{ikt+1}Y_{ljt+1}\frac{\exp\left(z_{ikt}\widehat{\gamma}_{GMM}^{2step}\right)\exp\left(z_{ljt}\widehat{\gamma}_{GMM}^{2step}\right)}{\exp\left(z_{ikt+1}\widehat{\gamma}_{GMM}^{2step}\right)\exp\left(z_{ljt+1}\widehat{\gamma}_{GMM}^{2step}\right)} \\
&\quad - Y_{ikt}Y_{ljt}Y_{ijt+1}Y_{lkt+1}\frac{\exp\left(z_{ijt}\widehat{\gamma}_{GMM}^{2step}\right)\exp\left(z_{lkt}\widehat{\gamma}_{GMM}^{2step}\right)}{\exp\left(z_{ijt+1}\widehat{\gamma}_{GMM}^{2step}\right)\exp\left(z_{lkt+1}\widehat{\gamma}_{GMM}^{2step}\right)}.
\end{aligned}$$

The standard errors for $\widehat{\gamma}_{GMM}^{2step}$ are the square roots of the diagonal elements of $\widehat{Var}\left[\widehat{\gamma}_{GMM}^{2step}\right]$.

2.4 The Application

2.4.1 Data

Data come from Liu (2009) as described in Chapter 1.[6] The panel dataset used in Chapter 1 covers 208 countries or regions for the period from 1948 to 2002. However, in Chapter 2, I only focus on 34 member countries of the Organisation for Economic Co-operation and Development (OECD)[7] for the period from 1995 (in which the WTO was established) to 2002 because of the computational burden.[8] In total, the number of observations is 6,416,256.[9]

Because my model includes time-varying exporter (importer) fixed effects and time-invariant country-pair fixed effects, I cannot include time-varying exporter specific variables such as log of exporter's GDP and log of exporter's GDP per capita, time-varying importer specific variables such as log of importer's GDP and log of importer's GDP per capita and time-invariant country-pair variables such as log of distance and whether the two countries share a border.[10] Only variables that vary by i, j and t are included in z_{ijt} in (2.1). These include the lagged dependent variable, Y_{ijt-1}, whether countries i and j are members of the same regional trade agreement in year t (RTA_{ijt}), and whether countries i and j have an alliance relationship in year t (ALI_{ijt}). Table 2.3 provides the summary statistics for these variables.

2.4.2 Estimation Results

I apply my estimator to investigate the persistence of trade flows and the effect of RTA on trade. Table 2.4 displays the estimation results. First, after controlling for time-varying exporter (importer) fixed effects and time-invariant country-pair fixed effects, the lagged dependent variable is still very important. The point estimate for the coefficient on the lagged dependent variable is 0.27 with a standard error of 0.09. This shows that trade flow in the current period is highly influenced by trade flow in the previous year. Another estimate of my interest is the coefficient on RTA_{ijt}. As expected, the sign is positive. However, the estimate is not significant. Finally, the estimate for the coefficient on ALI_{ijt} is negative, which goes against my expectation.

[6] I applaud Liu's generosity for posting his dataset online.

[7] See Table 2.1 for the list of OECD member countries.

[8] My observations are from 1996 to 2001 because the year 1995 is used only for a lagged dependent variable for the first year (the year 1996) and I need the year 2002 for the last year (the year 2001) for estimation.

[9] In the case of 34 exporter countries and 34 importer countries for 6 years, if there was no missing value, the number of observations would be 6,678,144(=34*33*32*31*6).

[10] Even though dummy variables such as whether both i and j are members of GATT/WTO in year t and whether both are members of the same currency in year t are time-varying country-pair specific variables, I cannot include them because my sample countries are OECD (developed) countries and the variables are almost time-invariant for the 6 years.

In my dynamic model, the lagged dependent variable explains a large portion of the dependent variable. Furthermore, because there is only one type of exporters and importers (developed countries) in the sample, there might be little variation in RTA_{ijt} and ALI_{ijt} for the same country pair over time. As a result, the impacts of these variables are not well identified.

2.4.3 Comparison with the PPML Estimator

To compare the results from my estimator to those of the popular PPML estimator, I estimated several alternative models. First, I tried to estimate the same model above using the PPML estimator in Stata. The panel data version of the Poisson regression estimator in Stata can only estimate models with one set of unobserved effects. I therefore set the country-pair (dyadic) fixed effects as the unobserved effects and use dummy variables for the exporter-year specific unobserved effects and the importer-year specific unobserved effects. As expected, the estimation failed to yield results because of the large number of dummy variables in the regression, or the incidental parameter problem.

I then estimate two simpler models with stronger assumptions. First, in model (2.14), I include exporter fixed effects (d_i), importer fixed effects (e_j) and year fixed effects ($year_t$) with the assumption $E\left[\varepsilon_{ijt}|z_{ijt}, d_i, e_j, year_t\right] = 1$,

$$Y_{ijt} = d_i * e_j * year_t * \exp\left(z_{ijt}\gamma\right) * \varepsilon_{ijt}. \tag{2.14}$$

To estimate this model using the PPML, I employed the cross-section version of the Poisson regression estimator in Stata and include dummy variables for exporter, importer and year fixed effects. Second, in model (2.15), I include only the country-pair (or dyadic) fixed effects (c_{ij}) and year fixed effects ($year_t$) with the assumption that $E\left[\varepsilon_{ijt}|z_{ijt}, c_{ij}, year_t\right] = 1$,

$$Y_{ijt} = c_{ij} * year_t * \exp\left(z_{ijt}\gamma\right) * \varepsilon_{ijt}. \tag{2.15}$$

To estimate this model using the PPML, I employed the panel data version of the Poisson regression estimator in Stata, setting c_{ij} as the unobserved effects and including dummy variable for the year fixed effects.

Table 2.5 summarizes estimation results for (2.14) and (2.15). Comparing the results from my estimator in Table 2.4 with those in Table 2.5, I see some similarities and differences between my estimator and the PPML. First, I find that the coefficient estimates on the lagged dependent variable in three models are all positive and significant. This shows the importance of including lagged dependent variables in gravity model estimation. Second, results from my estimator show that the lagged dependent variable has a much larger effect on trade volume than what the PPML results imply. Furthermore, my results show that a regional trade agreement does

not have a statistically significant effect and an alliance relationship has a negative effect on trade volume, while the PPML results show that both have a significant and positive effect on trade volume. These differences show that different modelling assumptions and estimators lead to quite different results in gravity model estimation. Therefore, it is important to use an estimator that relies on weaker assumptions.

2.5 Conclusion

In this chapter, I develop a method to estimate a dynamic gravity model with multiple sets of unobserved effects, with only the conditional mean assumption for the dependent variable. My method deals with the many zeros problem and allows for lagged dependent variables and time-varying exporter and importer fixed effects as well as time-invariant country-pair fixed effects. I found that trade flow in the previous period still has a large and positive effect on trade flow in the current period after controlling for multiple fixed effects. But it is not clear whether RTA and alliance relationship boost trade flow in the long run.

Table 2.1: List of OECD Member Countries

Australia	Japan
Austria	Korea
Belgium	Luxembourg
Canada	Mexico
Chile	Netherlands
Czech Republic	New Zealand
Denmark	Norway
Estonia	Poland
Finland	Portugal
France	Slovak Republic
Germany	Slovenia
Greece	Spain
Hungary	Sweden
Iceland	Switzerland
Ireland	Turkey
Israel	United Kingdom
Italy	United States

Table 2.2: Variable Definitions

Variable	Definition
RTA_{ijt}	whether i and j are members of the same regional trade agreement in year t
ALI_{ijt}	whether i and j have an alliance relationship
Y_{ijt}	export from country i to country j in year t (1995 real ten billion dollars)

Table 2.3: Summary Statistics

	Mean	Std. Dev.	Min	Max
Y_{ijt}	0.28	1.06	0	21.11
RTA_{ijt}	0.57	0.49	0	1
ALI_{ijt}	0.30	0.46	0	1
Y_{ijt-1}	0.27	1.04	0	21.11

Note: The number of ijt pairs: 7,722
The number of observations: 6,416,256
The original Y_{ijt} in Liu (2009) is scaled down to solve the singularity issue in the estimation. The unit of Y_{ijt} is ten billion dollars.

Table 2.4: Estimation Results

	Coefficient		Coefficient	
	Mean	Std. Err.	Mean	Std. Err
RTA_{ijt}	14.48	1.46×10^6	19.56	7.32×10^6
ALI_{ijt}	-3.68^{***}	0.20	-	-
Y_{ijt-1}	0.27^{***}	0.09	0.23^{***}	0.09

Note: The number of observations: 6,416,256
*(**, ***) denotes significance at the 10%(5%, 1%) level.

Table 2.5: PPML Estimation Results

	Coefficient		Coefficient	
	Mean	Std. Err.	Mean	Std. Err.
RTA_{ijt}	1.43^{***}	0.14	0.11^{***}	0.04
ALI_{ijt}	0.45^{***}	0.10	0.26^{***}	0.04
Y_{ijt-1}	0.10^{***}	0.02	0.06^{***}	0.01
Year Fixed Effects	Yes	Yes	Yes	Yes
Exporter Fixed Effects	Yes	Yes	No	No
Importer Fixed Effects	Yes	Yes	No	No
Dyadic Fixed Effects	No	No	Yes	Yes
Num of Obs	7,722		7,684	

Note: *(**, ***) denotes significance at the 10%(5%, 1%) level.

Chapter 3

The Impact of Banking Crisis on International Trade in Services

3.1 Introduction

Many studies have attempted to explain how financial crises affect international trade flows, since the collapse in trade during the 2007-2008 global recession was sudden and severe both relative to the decline in GDP as well as in absolute terms. Most of the existing literature has focused on the impact of a banking crisis on international trade in goods. However, the world economy is increasingly characterized as a service economy, as more and more developed and developing countries become industrialized and then post-industrialized.[1] Moreover, the recent cost reduction in information and communication technologies has accelerated this process (e.g., Amiti and Wei 2009; Francois and Hoekman 2010; Kandilov and Grennes 2010). International trade in services is also growing faster than international trade in goods. However, despite the growing importance of the services trade, only a few papers have attempted to investigate the effect of financial crises on services trade. This reflects the fact that, until recently, no internationally comparable bilateral services trade data were available. The OECD now provides bilateral services trade data, and it is thus possible to examine the effect of the recent global crisis on services trade. In this chapter, I investigate the effects of banking crises on services trade by using bilateral sectoral services trade as well as bilateral total services trade covering 60 countries over 5 years from 2005 to 2009.[2] To the best of my knowledge, no other study has examined these effects by using bilateral services trade flows for a relatively broad range of countries.

[1] As incomes increase, the demand for agricultural products reaches its limit and the demand for industrial goods and services increases.

[2] I focus on a banking crisis rather than a currency crisis because a banking crisis is the direct source of the exporter's credit crunch.

First, I discuss recent studies on the effect of financial crises on international trade. Although services trade has different characteristics than goods trade, considering that a large component of services trade is related to goods trade, I review the existing literature on goods trade. Moreover, most international trade theory can apply equally to goods trade and services trade in principle.

Ma and Cheng (2003) show the negative impact of financial crises on international trade using aggregate bilateral trade data from 1981 to 1998. However, the channel through which financial crises impact international trade is not clear. Many economists argue that three aspects of a financial crisis can cause international trade to collapse.

The first is the demand side explanation. When a financial crisis unfolds, the importer country's demand for foreign goods as well as domestic goods will shrink due to the loss of income and the poor economic outlook. Using a general equilibrium model, Eaton *et al.* (2014) find that demand shocks during a financial crisis are the main contributor to the reduction in international trade. Levchenko, Lewis and Tesar (2010) also argue that sectors with larger reductions in domestic output had larger drops in international trade, but there is no support for the hypothesis that trade credit played an important role in the 2008-2009 trade collapse. However, weakness in demand is not the only source of international trade collapse during the financial crisis. Ahn, Amiti and Weinstein (2011) find that calibration results from a model without financial frictions underestimate the decline in international trade. They find the demand side explanation accounts for only 70-80% of the decline in international trade.

The second explanation focuses on the production side. The credit crunch during a financial crisis will restrict the exporter's activity. Amiti and Weinstein (2011) note that exporters are more sensitive to financial shocks than domestic firms due to the higher default risk and higher working capital requirements. Using Japanese bank-level data from 1990 to 2010, they find that the health of banks providing trade finance is important to firm-level exports during financial crises. Chor and Manova (2012), using data on monthly US imports disaggregated by partner exporter and sector from January 2007 to July 2009, find that countries with tighter credit markets exported less to the US during a financial crisis and that the exports of financially vulnerable industries were more sensitive to the cost of external capital. Iacovone and Zavacka (2009) focus on the impact of banking crises on manufacturing exports, using exports data disaggregated by 81 industries from 1980 to 2006. They find that the exports of sectors more dependent on external finance grow less than other sectors [3] They also emphasize the importance of a healthy financial system for exports growth. Ahn, Amiti and Weinstein (2011) show that export prices rose relative to domestic manufacturing prices. They also explain why many studies fail to find a relationship between dependence on external finance and US imports

[3]Note that Iacovone and Zavacka (2009) use the data on exports from A (one exporter) to the World (all importers), not bilateral trade.

through the fact that import prices in sectors with high dependence on external finance rose by much more than the prices in other sectors in the US.

The third explanation is protectionism. To stimulate domestic economic activity, countries will have more incentive to protect domestic firms by increasing protectionism during a global recession triggered by a financial crisis. Kee, Neagu and Nicita (2013) quantify trade policy changes and the associated effects for about 100 countries between 2008 and 2009. They find that there has been no widespread increase in protectionism. Only a few countries such as Russia, Malawi, Argentina, Turkey and China raised their tariffs significantly. The EU and US increased antidumping duties. They argue that trade policy changes can explain less than 2% of the decline in international trade during a financial crisis. Eaton *et al.* (2014) argue that little of the international trade collapse resulted from increased trade barriers including credit crunch or protectionism. However, Barfield (2009) observes that many countries have provided stimulus packages to aid their industries and citizens in the face of the global economic crisis and recession. (e.g., government procurement and "buy domestic"). It is challenging to measure the impact of such non-tariff barriers due to the limited availability of data.

Kiendrebeogo (2013) analyzes the effect of banking crises on bilateral goods trade over the period 1988-2010.[4] He concludes that both the exporter's and the importer's banking crises are associated with a decline in bilateral goods trade. However, it is not clear that banking crises have the same effects on services trade, because services trade has different characteristics than goods trade, and the trade of particular sectors within services is heterogeneous. Borchert and Mattoo (2009)[5] argue that the impact of a banking crisis on services trade is relatively small compared to the collapse of goods trade after banking crises. They also provide several reasons why services trade responds differently than goods trade to banking crises. On the demand side, services are less cyclical than goods because services are not storable and less subject to the big decline in demand during banking crises. On the supply side, services trade might be less dependent on external finance because services-producing firms have limited tangible collateral. Biewen, Harsch and Spies (2012), using data on service imports of German multinationals from 2002 to 2008, find that financial constraints during banking crises do not have any significant effect on services trade. And, they argue that the crisis-resilience of services trade is related to the increased level of service offshoring due to internal cost pressures.

In this study, I use annual bilateral sectoral services trade data[6] as well as bilateral total services trade data which cover 60 countries (see Appendix C) from 2005 to 2009. I focus on other commercial services trade because it is the largest sector of total services trade (Kandilov

[4]Data on bilateral trade come from the United Nation's COMTRADE database.

[5]They use the US exports and imports of services.

[6]OECD breaks down services trade data into the sectors of travel, transportation, government and other commercial services. In this study, I use other commercial services trade, travel services trade, transportation services trade and total services trade for the empirical analysis.

and Grennes 2012) as well as the most rapidly growing sector (Hoekman 2006). Moreover, other commercial services trade is at the center of the recent debate on service offshoring.[7] In my estimation, I use the gravity equation employing the Poisson pseudo maximum likelihood (PPML) estimator to avoid sample selection bias produced by OLS (see Santos Silva and Tenreyro 2006).

I hypothesize that the exporter's and the importer's banking crises affect each service sector's trade differently. In my empirical investigation, I find that both the exporter's and the importer's banking crises affect bilateral services trade negatively. When both countries are in a banking crisis, the negative effect is even larger. I discover similar results for transportation services trade. However, my findings suggest that there are no significant effects of banking crises on travel services trade.[8]

The remaining part of this chapter is organized as follows. Section 2 describes the data I use for estimation. I explain my econometric strategy in Section 3 and discuss the results in Section 4. Section 5 concludes.

3.2 Data

Data on international trade in services are obtained from the OECD. Annually, the OECD provides bilateral services trade data for 34 OECD countries. These countries report their bilateral services trade data with their partner countries including non-OECD countries as well as OECD countries.[9] Therefore, the OECD does not provide bilateral services trade data between non-OECD countries. In the case of bilateral services trade between OECD members, the trade data are available not only from the exporter but also from the importer.[10] In general, the exporter country and the importer country do not report the same value for bilateral services trade flow. Many empirical studies on bilateral goods trade suggest that import data are more reliable than export data because countries are more interested in tracking imports for the purpose of tariff collections.[11] Kandilov and Grennes (2012) suggest that it should not make much difference whether I use the importer's report or the exporter's report.[12] Following Kandilov and Grennes (2012), if there is information from both the exporter and the importer

[7]Head, Mayer and Ries (2009) note that the main idea of service offshoring is that a firm can replace the services of domestic workers with the services of workers residing in foreign countries.

[8]Travel services cover expenses for goods and services acquired by a person during his/her visit in a country other than his/her own. If the stay of a person is for more than one year, he/she is considered to be a resident of the visited economy. (The World Bank)

[9]See Appendix C: List of Countries for sample countries.

[10]Let Y_{ijt} denote the services exports from country i to country j ($i \neq j$) in year t. If both i and j are OECD member countries, Y_{ijt} appears twice a year corresponding to the imports of j from i and vice versa. For 1,657 observations (from a total of 9,700), bilateral services trade flows are available from both the exporter and the importer.

[11]See Liu (2009) for more details.

[12]When Kandilov and Grennes (2012) regress the exporter-reported services trade value on the importer-reported services trade value, they find that the estimated coefficient is close to one.

for a bilateral trade flow, I use the importer's report. The OECD provides total services trade which comprises transportation services trade, travel services trade, government services trade and other commercial services trade (which comprises financial, insurance, computer, communication, information and business services trade). I focus on other commercial services trade in this study.[13] As mentioned, other commercial services trade is closely related to goods trade and is the largest component of total services trade. Moreover, it is the main subject of the recent offshoring debate. The other commercial services trade data cover 60 countries over 5 years from 2005 to 2009.[14]

To estimate the gravity equation, I collect data on the exporter's and importer's GDP[15], the bilateral distance between the exporter and importer, common language which equals one if both the exporter and the importer have the same language and zero otherwise. I control for common legal origin, which equals one if both the exporter and importer have the same legal origin and zero otherwise (see Stein and Daude 2007; Head, Mayer and Ries 2009; Kandilov and Grennes 2010).[16] I also control for the exporter's and importer's Internet users (per 100 people) as well as the exporter's and importer's rule of law, which reflects the quality of institutions ranging from -2.5 (weak) to 2.5 (strong), because I think that the Internet lowers communication costs and reliable legal institutions facilitate services trade by reducing business contracts costs and dispute settlement costs (see Berkowitz, Moenius and Pistor 2006; Kandilov and Grennes 2010).[17] Data on banking crises are from Laven and Valencia (2013).[18] See Table 3.2 for summary statistics on all variables.

3.3 Econometric Strategy

I employ the gravity equation which has been widely used in the empirical trade literature since Tinbergen (1962) to investigate how banking crises affect bilateral services trade. The gravity equation has been very successful in explaining the determinants of bilateral goods trade, and recently it has also been used to explain the determinants of services trade (e.g., Mirza and Nicoletti 2004; Kimura and Lee 2006; Head, Mayer and Ries 2009, 2010; Kandilov and Grennes 2010, 2012). Head, Mayer and Ries (2009) provide a theoretical foundation for using the gravity

[13] I also address estimation results on total services trade, transportation services trade and travel services trade.

[14] The financial crisis that is considered to have been one of the worst financial crises since the Great Depression of the 1930s occurred in 2007.

[15] The Exporter's GDP and the importer's GDP come from the World Bank's World Development Indicators (WDI) database.

[16] Distance, common language and common legal origin come from the CEPII database.

[17] Data on Internet users and the rule of law come from the World Bank.

[18] Laven and Valencia (2013) study all systemic banking crises during the period 1970-2011.

equation to analyze the determinants of bilateral services trade.[19]

Basically, the gravity equation states that trade flows from one country to another are proportional to the product of the two countries' GDPs and inversely proportional to various trade barriers including the distance between the two countries. In a panel data setting, the theoretical and empirical formulation of the gravity equation is equivalent to

$$Y_{ijt} = \frac{\alpha_0 GDP_{it}^{\alpha_1} GDP_{jt}^{\alpha_2} \exp\left(\alpha_4 z_{ijt}\right) \varepsilon_{ijt}}{DIST_{ij}^{\alpha_3}}. \tag{3.1}$$

In (3.1), Y_{ijt} denotes services exports from country i to country j ($i \neq j$) in year t, $GDP_{i(j)t}$ is the exporter i's (the importer j's) GDP in year t, $DIST_{ij}$ is the distance between i and j, z_{ijt} is a set of observed trade barrier or facilitation variables, ε_{ijt} is an i.i.d. error term with $E\left[\varepsilon_{ijt}|GDP_{it}, GDP_{jt}, DIST_{ij}, z_{ijt}\right] = 1$ and α's are the parameters to be estimated.

The gravity equation (3.1) can be reexpressed as (3.2) below by log-linearization and the following equation can be estimated via OLS.

$$\log Y_{ijt} = \log \alpha_0 + \alpha_1 \log GDP_{it} + \alpha_2 \log GDP_{jt} - \alpha_3 \log DIST_{ij} + \alpha_4 z_{ijt} + \log \varepsilon_{ijt}. \tag{3.2}$$

There are several econometric issues in using the gravity equation (3.2). First, because the gravity equation (3.2) omits the multilateral resistance terms specified by Anderson and Van Wincoop (2003), estimates might be biased (omitted variable bias). Feenstra (2004) suggests including the time-varying exporter and importer fixed effects to take into account multilateral resistance when panel data are used. However, because of the inclusion of the exporter's and importer's banking crisis variables, which are time-varying, I cannot use the time-varying exporter and importer fixed effects. Alternatively, I include time-invariant exporter and importer fixed effects and year fixed effects in my baseline model to control for multilateral resistance.

Next, in (3.2), I cannot include zero trade flows because I cannot take a log of zero. If I drop zero trade flows, my estimates might be biased (sample selection bias). Moreover, heteroskedasiticity is believed to be a prevalent feature of trade data. Therefore, if the expected value of $\log \varepsilon_{ijt}$ depends on explanatory variables in (3.2), it delivers biased estimates. Santos Silva and Tenreyro (2006) suggest the Poisson pseudo maximum likelihood (PPML) estimator as a solution to deal with these econometric problems. They argue that this is the most robust estimation method to solve these problems. The PPML estimator can be implemented by solving

[19] See Anderson (1979), Helpman and Krugman (1985), Deardoff (1998), Eaton and Kortum (2002) and Olivero and Yotov (2012) for the micro-foundations of the gravity equation.

the following set of first-order conditions (3.3).

$$\sum_{k=1}^{n}\left[Y_k - \exp\left(x_k\widehat{\beta}\right)\right] * x_k = 0, \tag{3.3}$$

where Y_k is bilateral services trade of observation k, x_k is the vector of explanatory variables, n is the number of observations and $\widehat{\beta}$ are the parameter estimates. Note that the PPML estimates are consistent provided that $\exp\left(x_k\widehat{\beta}\right)$ is the correct specification of the conditional mean of Y_k given x_k, that is, $E\left[Y_k|x_k\right] = \exp\left(x_k\widehat{\beta}\right)$.[20] Following Santos Silva and Tenreyro (2006), I use the PPML estimator in this study.

One of the remaining econometric concerns noted in the banking crisis literature is the endogeneity problem driven by reverse causality. Iacovone and Zavacka (2009) point out the possibility that the drop in exports is the cause of a banking crisis rather than the other way round. However, because my interest is in bilateral services trade and I include a set of fixed effects, I believe that the endogeneity problem is not a major concern in this study.

My baseline model is

$$Y_{ijt} = \exp\left(\begin{array}{c}\alpha_1 \log GDP_{it} + \alpha_2 \log GDP_{jt} - \alpha_3 \log DIST_{ij} + \alpha_4 z_{ijt} \\ +\alpha_5 BC_{it} + \alpha_6 BC_{jt} + \mu_i + \mu_j + \tau_t\end{array}\right) * \varepsilon_{ijt}, \tag{3.4}$$

where $BC_{i(j)t}$ is a dummy variable which is equal to one if the exporter i (the importer j) experiences a banking crisis in year t and zero otherwise, $\mu_{i(j)}$ is the exporter i's (the importer j's) time-invariant fixed effects, τ_t is year fixed effects and ε_{ijt} is an i.i.d. error term with $E\left[\varepsilon_{ijt}|GDP_{i(j)t}, DIST_{ij}, z_{ijt}, BC_{i(j)t}, \mu_{i(j)}, \tau_t\right] = 1$. I include banking crisis dummies for the importer as well as the exporter because I anticipate that the exporter's banking crisis and the importer's banking crisis may affect bilateral services trade in different ways. I will also consider the case in which both the exporter and the importer fall into a banking crisis at the same time.[21] In this case, I expect that bilateral services trade declines more significantly, because both countries experience difficulties in providing trade credit. Moreover, I test whether the effects of banking crises at different per capita income levels are different.[22]

To check for robustness, I also use a country-pair (dyadic) fixed effects model with year

[20] Statistical inference is based on a White robust covariance matrix estimator.

[21] I add the dummy variable $BCBOTH_{ijt}$ which is equal to one if both exporter i and importer j fall into banking crisis in year t and zero otherwise. Note that I set $BC_{it} = 0$ and $BC_{jt} = 0$ if $BCBOTH_{ijt} = 1$ to uncover the net effect of a banking crisis when both the exporter and the importer experience a banking crisis in the same year.

[22] I add a term for interaction ($BC_{i(j)t} * NH\ Income_{i(j)}$) between exporter's (or importer's) banking crisis dummy variable ($BC_{i(j)t}$) and non-high income country dummy variable ($NH\ Income_{i(j)}$). Therefore, the base category (the coefficient on $BC_{i(j)t}$) is high income country when I add the interaction terms.

fixed effects (3.5).

$$Y_{ijt} = \exp\left(\begin{array}{c} \alpha_1 \log GDP_{it} + \alpha_2 \log GDP_{jt} - \alpha_3 \log DIST_{ij} + \alpha_4 z_{ijt} \\ +\alpha_5 BC_{it} + \alpha_6 BC_{jt} + \mu_{ij} + \tau_t \end{array} \right) * \varepsilon_{ijt}. \tag{3.5}$$

In equation (3.5), I cannot include time-invariant country-pair variables (e.g., distance, common language and common legal origin) as explanatory variables because I use dyadic fixed effects (μ_{ij}), which absorb time-invariant heterogeneity. I also control for a time trend by including a full set of year dummies (τ_t).[23]

3.4 Results and Discussion

3.4.1 Main Results: Other Commercial Services Trade

Table 3.3 and Table 3.4 summarize the estimation results for model (3.4) and model (3.5). As discussed in Section 3, Table 3.3 reports the estimation results for the model using time-invariant exporter fixed effects, time-invariant importer fixed effects and year fixed effects. And, Table 3.4 reports the estimation results for the model using time-invariant country-pair (dyadic) fixed effects and year fixed effects. My goal is to estimate the effect of banking crises on other commercial services trade. The exporter's banking crisis dummy will capture the effect of banking crises as supply-side shocks on services trade, and the importer's banking crisis dummy will capture the effect of banking crises as demand-side shocks on services trade.

Column (1) of Table 3.3 and Table 3.4 reports these two effects of banking crises. In column (2) of Table 3.3 and Table 3.4, I include an interaction between the exporter's and the importer's banking crisis dummies to capture the detrimental effects of banking crises when both the exporter and the importer are experiencing a banking crisis at the same time. Finally, I investigate how the exporter's and the importer's banking crises affect services trade differently at different per capita income levels. Column (3) of Table 3.3 and Table 3.4 reports the estimation results for high income exporter's and importer's banking crises and the non-high income exporter's and importer's banking crises separately.

I begin my analysis by investigating the main explanatory variables of the gravity equation. I will focus on the baseline specification (column (1) of Table 3.3). The coefficients on the exporter's GDP, the importer's GDP and the distance are 0.52, 0.41 and -0.56 respectively. All are statistically significant. These results are consistent with much of the existing literature.

[23] I use Stata as the statistical software in this study. In Stata, there is no way to estimate a multiple fixed effects model such as (3.4) using a transformation method to remove multiple fixed effects. Therefore, I use each dummy variable to control for exporter, importer and year fixed effects in (3.4).

For (3.5), I can remove country-pair fixed effects through transformation in Stata. Additionally, I include a year dummy to control for year fixed effects.

As expected, common legal origin has a positive and significant effect (0.28) on services trade. However, the coefficient estimate on common language (0.09) is not statistically significant. The estimated impact of exporter's rule of law is positive (0.15) and significant. This means that the exporter's quality of legal institutions is an important determinant of other commercial services trade. However, all other estimated impacts of the importer's rule of law and the exporter's and the importer's Internet users are not significant.

In column (1) of Table 3.3 and Table 3.4, the coefficient estimate on the exporter's banking crisis is -0.04 and statistically significant. In the case of the importer's banking crisis, although both Tables report the same coefficient estimates (-0.04), the estimate is statistically significant only in Table 3.4.[24] This suggests that the exporter's and the importer's banking crises are associated with an approximately 4% decline in bilateral services trade. In column (2) of Table 3.3 and Table 3.4, the coefficient estimates on the interaction between the exporter's and the importer's banking crises are -0.08 and -0.07, respectively, and statistically significant at 5%. This shows a detrimental negative effect of banking crises on bilateral services trade when both the exporter and the importer are experiencing a banking crisis. However, when I control for the interaction between the exporter's and the importer's banking crises, the net effects of the exporter's and the importer's banking crises are no longer significant. In column (3) of Table 3.3 and Table 3.4, the estimation results for the high income exporter's and the high income importer's banking crises are similar to the coefficient estimates on the exporter's and the importer's banking crises in column (1) of Table 3.3 and Table 3.4. But the estimation results for non-high income countries' banking crises are not statistically significant. In this study, however, I cannot say that only high income countries' banking crises have a detrimental effect on bilateral services trade. Note that most banking crises in the sample occur in high income countries.[25] If I were able to collect a larger dataset on banking crises and bilateral service trade patterns, it might be possible at some future date to reveal the effect of banking crises on bilateral services trade between countries having different income levels.

3.4.2 Different Services Trade: Transportation and Travel

Next, the focus shifts to different categories of services trade, and specifically transportation and travel services trade. Because the results of the baseline model including exporter, importer and year fixed effects are similar to the results of the other model including country-pair (dyadic) and year fixed effects, I only focus on the results of the baseline model that include exporter, importer and year fixed effects for the analysis of transportation and travel services trade.

[24]The difference in the standard error of coefficient estimates on the importer's banking crisis in column (1) of Table 3.3 and Table 3.4 is very small.

[25]In the sample countries, only two non-high income countries (Hungary, Nigeria) have experienced banking crises recently. These data restrictions limit my analysis.

First, because transportation services determine how efficiently goods move from producers to consumers, the performance of transportation services trade might be related to goods trade. Therefore, I anticipate that when banking crises occur, transportation services trade might exhibit a similar pattern to goods trade or other commercial services trade. Table 3.5 reports estimation results for transportation services trade. Banking crises specifications of columns (1), (2) and (3) in Table 3.5 for transportation services trade are the same as in (1), (2) and (3) in Table 3.3 for other commercial services trade, respectively. The coefficients on the exporter's GDP, the importer's GDP and the distance are 0.17, 0.60 and -0.51, respectively, all of which are significant. I find that the coefficient on the exporter's GDP for transportation services trade (0.17) is relatively smaller than for other commercial services trade (0.52). The exporter's economic size is a relatively less important determinant of transportation services trade than of other commercial services trade. As expected, the impact of exporter's and importer's banking crises on bilateral transportation services trade are similar to other commercial services trade. When both the exporter and the importer are in a banking crisis at the same time, banking crises lead to about a 11% decline in transportation services trade. See Table 3.5 for other estimation results on transportation services trade.

Next, I turn to travel services trade. Compared to goods-related services such as other commercial services and transportation services, travel services are relatively heterogeneous. Table 3.6 displays estimation results for travel services trade. The most interesting result is that the coefficient estimate on the importer's GDP (1.04) is 5 times lager than the coefficient estimate on the exporter's GDP (0.20).[26] This means that the demand side for travel services is a more important determinant of bilateral travel services trade than the supply side. The distance effect (-0.86) is much larger than for other commercial services trade (-0.56) and transportation services trade (-0.51). Finally, I find that the effect of banking crises on bilateral travel services trade is not significant. See Table 3.6 for other estimation results on travel services trade.[27]

3.5 Conclusion

Many studies have sought to explain how financial crises affect international trade flows. Despite the growing importance of services trade, most of the existing literature has focused on the impact of banking crises on international trade in goods. Recent empirical work finds that both the exporter's and the importer's banking crises are associated with a decline in bilateral goods

[26]The ratio of coefficient estimates on the exporter's GDP (0.52) and the importer's GDP (0.41) for other commercial services trade is 0.79 ($=\frac{0.41}{0.52}$). For transportation services, the ratio is 3.53($=\frac{0.60}{0.17}$).

[27]Table 3.7 presents the estimation results for total services trade. I do not include interpretations of the estimation results for total services trade here. Because the various sectors within services are heterogeneous (Eichengreen and Gupta 2011), the analysis of sectoral services trade is more meaningful because I can adjust for confounding factors.

trade. However, it is not clear whether banking crises have the same effects on services trade, because services trade has different characteristics than goods trade.

I investigate the effect of banking crises on services trade by using OECD bilateral services trade data covering 60 countries from 2005 to 2009. I hypothesize that the exporter's and the importer's banking crises affect trade in each services sector differently because sectoral services are heterogeneous. I find that both the exporter's and the importer's banking crises have a negative effect on services trade that is related to goods trade, such as other commercial services trade and transportation services trade. When both the exporter and the importer are in the midst of a banking crisis, the effect is even more detrimental. However, there is no significant effect of banking crises on travel services trade.

Table 3.1: Variable Definitions

Variable	Definition
Y_{ijt}	other commercial services export from i to j in year t (current million dollars)
log GDP_{it}	log of current GDP of i (exporter country) in year t (current dollars)
log GDP_{jt}	log of current GDP of j (importer country) in year t (current dollars)
log $Distance_{ij}$	log of distance between i and j (km)
Banking $Crisis_{it}$	i falls into banking crisis in year t
Banking $Crisis_{jt}$	j falls into banking crisis in year t
Banking Crisis $Both_{ijt}$	Both i and j fall into banking crises in year t
NH $Income_{i}$	i is non-high income country
NH $Income_{j}$	j is non-high income country
Common $Language_{ij}$	i and j use the same language
Common Legal $Origin_{ij}$	i and j have the common legal origin
Rule of Law_{it}	the quality of i's gevernance in year t (from -2.5 to 2.5)
Rule of Law_{jt}	the quality of j's gevernance in year t (from -2.5 to 2.5)
Internet $User_{it}$	the number of i's internet user per 100 people
Internet $User_{jt}$	the number of j's internet user per 100 people

Table 3.2: Summary Statistics

Variable	Observation	Mean	Std.Dev.	Min	Max
Y_{ijt}	8,043	642.31	2139.40	0	32,882
log GDP_{it}	8,043	26.76	1.41	23.27	30.32
log GDP_{jt}	8,043	26.77	1.42	23.27	30.32
Log $Distance_{ij}$	8,043	8.20	1.11	4.09	9.87
Banking $Crisis_{it}$	8,043	0.20	0.40	0	1
Banking $Crisis_{jt}$	8,043	0.20	0.40	0	1
Common $Language_{ij}$	8,043	0.08	0.26	0	1
Common Legal $Origin_{ij}$	8,043	0.21	0.41	0	1
Rule of Law_{it}	8,043	0.96	0.87	-1.6	2
Rule of Law_{jt}	8,043	0.96	0.87	-1.6	2
Internet $User_{it}$	8,043	55.49	24.20	2.39	93
Internet $User_{jt}$	8,043	55.52	24.17	2.39	93

Note: Sample periods covers 2005 - 2009.

Table 3.3: Effects of Banking Crisis on Other Commercial Services Trade

	(1)	(2)	(3)
log GDP_{it}	0.52***(0.10)	0.51***(0.11)	0.51***(0.10)
log GDP_{jt}	0.41***(0.10)	0.41***(0.10)	0.41***(0.10)
log $DIST_{ij}$	-0.56***(0.04)	-0.56***(0.04)	-0.56***(0.04)
Banking $Crisis_{it}$	-0.04*(0.03)	-0.04(0.03)	-0.04*(0.02)
Banking $Crisis_{jt}$	-0.04(0.03)	-0.04(0.06)	-0.04*(0.03)
Banking Crisis $Both_{ijt}$	-	-0.08**(0.04)	-
Banking $Crisis_{it}$*NH $Income_{i}$	-	-	0.06(0.09)
Banking $Crisis_{jt}$*NH $Income_{j}$	-	-	0.05(0.03)
Common $Language_{ij}$	0.09(0.10)	0.09(0.10)	0.09(0.10)
Common Legal $Origin_{ij}$	0.28***(0.10)	0.28***(0.10)	0.28***(0.10)
Rule of Law_{it}	0.15*(0.09)	0.15*(0.09)	0.15*(0.09)
Rule of Law_{jt}	0.03(0.10)	0.03(0.10)	0.03(0.10)
Internet $User_{it}$×10	0.001(0.02)	0.002(0.02)	0.0005(0.02)
Internet $User_{jt}$×10	-0.02(0.02)	-0.01(0.02)	-0.02(0.02)
Year Fixed Effects	Yes	Yes	Yes
Exporter Fixed Effects	Yes	Yes	Yes
Importer Fixed Effects	Yes	Yes	Yes
Dyadic Fixed Effects	No	No	No
Pseudo R^2	0.91	0.91	0.91
Observations	8,043	8,043	8,043

Note: Heteroskedasticity-robust standard errors in parentheses
*(**, ***) denotes significance at the 10%(5%, 1%) level

Table 3.4: Effects of Banking Crisis on Other Commercial Services Trade

	(1)	(2)	(3)
log GDP_{it}	0.55^{***}(0.09)	0.53^{***}(0.09)	0.55^{***}(0.09)
log GDP_{jt}	0.40^{***}(0.08)	0.39^{***}(0.08)	0.40^{***}(0.08)
log $DIST_{ij}$	-	-	-
Banking $Crisis_{it}$	-0.04^{*}(0.02)	-0.008(0.02)	-0.04^{*}(0.02)
Banking $Crisis_{jt}$	-0.04^{*}(0.02)	0.006(0.03)	-0.04^{*}(0.02)
Banking Crisis $Both_{ijt}$	-	-0.07^{**}(0.03)	-
Banking $Crisis_{it}$*NH $Income_{i}$	-	-	0.06(0.08)
Banking $Crisis_{jt}$*NH $Income_{j}$	-	-	0.04(0.05)
Common $Language_{ij}$	-	-	-
Common Legal $Origin_{ij}$	-	-	-
Rule of Law_{it}	0.24^{**}(0.10)	0.24^{**}(0.10)	0.25^{**}(0.10)
Rule of Law_{jt}	0.08(0.10)	0.07(0.10)	0.08(0.10)
Internet $User_{it}\times100$	0.01(0.3)	0.02(0.3)	0.002(0.3)
Internet $User_{jt}\times100$	-0.04(0.2)	-0.03(0.2)	-0.05(0.2)
Year Fixed Effects	Yes	Yes	Yes
Exporter Fixed Effects	No	No	No
Importer Fixed Effects	No	No	No
Dyadic Fixed Effects	Yes	Yes	Yes
Pseudo R^2	0.99	0.99	0.99
Observations	7,636	7,636	7,636

Note: Heteroskedasticity-robust standard errors in parentheses
*(**, ***) denotes significance at the 10%(5%, 1%) level

Table 3.5: Effects of Banking Crisis on Transportation Services Trade

	(1)	(2)	(3)
log GDP_{it}	0.17**(0.09)	0.16*(0.09)	0.17*(0.09)
log GDP_{jt}	0.60***(0.12)	0.60***(0.13)	0.61***(0.12)
log $DIST_{ij}$	-0.51***(0.04)	-0.51***(0.04)	-0.51***(0.04)
Banking $Crisis_{it}$	-0.04**(0.02)	-0.01(0.04)	-0.04**(0.02)
Banking $Crisis_{jt}$	-0.07*(0.04)	-0.04(0.05)	-0.07*(0.04)
Banking Crisis $Both_{ijt}$	-	-0.11**(0.05)	-
Banking $Crisis_{it}$*NH $Income_i$	-	-	0.13**(0.07)
Banking $Crisis_{jt}$*NH $Income_j$	-	-	0.12***(0.02)
Common $Language_{ij}$	0.14(0.11)	0.14(0.11)	0.14(0.11)
Common Legal $Origin_{ij}$	0.10(0.09)	0.10(0.09)	0.10(0.09)
Rule of Law_{it}	-0.06(0.09)	-0.06(0.06)	-0.06(0.06)
Rule of Law_{jt}	-0.25*(0.14)	-0.24*(0.14)	-0.24*(0.14)
Internet $User_{it}$×10	-0.02(0.02)	-0.01(0.02)	-0.02(0.02)
Internet $User_{jt}$×10	-0.01(0.03)	-0.01(0.03)	-0.01(0.03)
Year Fixed Effects	Yes	Yes	Yes
Exporter Fixed Effects	Yes	Yes	Yes
Importer Fixed Effects	Yes	Yes	Yes
Dyadic Fixed Effects	No	No	No
Pseudo R^2	0.84	0.84	0.84
Observations	8,495	8,495	8,495

Note: Heteroskedasticity-robust standard errors in parentheses
*(**, ***) denotes significance at the 10%(5%, 1%) level

Table 3.6: Effects of Banking Crisis on Travel Services Trade

	(1)	(2)	(3)
log GDP_{it}	0.20**(0.08)	0.19**(0.08)	0.20**(0.08)
log GDP_{jt}	1.04***(0.11)	1.03***(0.10)	1.03***(0.11)
log $DIST_{ij}$	-0.86***(0.06)	-0.87***(0.06)	-0.86***(0.06)
Banking $Crisis_{it}$	-0.002(0.01)	0.01(0.05)	-0.001(0.01)
Banking $Crisis_{jt}$	0.03(0.03)	0.05(0.06)	0.03(0.03)
Banking Crisis $Both_{ijt}$	-	0.03(0.03)	-
Banking $Crisis_{it}$*NH $Income_i$	-	-	-0.004(0.05)
Banking $Crisis_{jt}$*NH $Income_j$	-	-	0.29***(0.02)
Common $Language_{ij}$	0.71***(0.14)	0.71***(0.14)	0.71***(0.14)
Common Legal $Origin_{ij}$	0.19*(0.11)	0.19*(0.11)	0.19*(0.11)
Rule of Law_{it}	0.03(0.07)	0.03(0.07)	0.03(0.07)
Rule of Law_{jt}	-0.07(0.10)	-0.07(0.10)	-0.06(0.10)
Internet $User_{it}\times10$	-0.01(0.02)	-0.01(0.02)	-0.01(0.02)
Internet $User_{jt}\times10$	-0.0003(0.02)	0.0003(0.01)	-0.004(0.02)
Year Fixed Effects	Yes	Yes	Yes
Exporter Fixed Effects	Yes	Yes	Yes
Importer Fixed Effects	Yes	Yes	Yes
Dyadic Fixed Effects	No	No	No
Pseudo R^2	0.87	0.87	0.87
Observations	9,672	9,672	9,672

Note: Heteroskedasticity-robust standard errors in parentheses
*(**, ***) denotes significance at the 10%(5%, 1%) level

Table 3.7: Effects of Banking Crisis on Total Services Trade

	(1)	(2)	(3)
log GDP_{it}	0.28^{***}(0.05)	0.28^{***}(0.05)	0.28^{***}(0.05)
log GDP_{jt}	0.58^{***}(0.09)	0.58^{***}(0.09)	0.58^{***}(0.09)
log $DIST_{ij}$	-0.63^{***}(0.04)	-0.63^{***}(0.04)	-0.63^{***}(0.04)
Banking $Crisis_{it}$	-0.008^{*}(0.02)	-0.01(0.03)	-0.007(0.02)
Banking $Crisis_{jt}$	-0.008(0.02)	-0.01(0.04)	-0.009(0.02)
Banking Crisis $Both_{ijt}$	-	-0.02(0.03)	-
Banking $Crisis_{it}$*NH $Income_{i}$	-	-	-0.06(0.03)
Banking $Crisis_{jt}$*NH $Income_{j}$	-	-	0.04(0.05)
Common $Language_{ij}$	0.42^{***}(0.11)	0.42^{***}(0.10)	0.42^{***}(0.11)
Common Legal $Origin_{ij}$	0.16^{**}(0.08)	0.16^{**}(0.08)	0.16^{**}(0.08)
Rule of Law_{it}	0.11^{**}(0.04)	0.11^{**}(0.04)	0.11^{**}(0.04)
Rule of Law_{jt}	-0.05(0.09)	-0.05(0.09)	-0.05(0.09)
Internet $User_{it} \times 100$	-0.09(0.09)	-0.09(0.09)	-0.08(0.09)
Internet $User_{jt} \times 100$	0.04(0.2)	0.04(0.2)	0.03(0.2)
Year Fixed Effects	Yes	Yes	Yes
Exporter Fixed Effects	Yes	Yes	Yes
Importer Fixed Effects	Yes	Yes	Yes
Dyadic Fixed Effects	No	No	No
Pseudo R^2	0.92	0.92	0.92
Observations	32,873	32,873	32,873

Note: Heteroskedasticity-robust standard errors in parentheses
*(**, ***) denotes significance at the 10%(5%, 1%) level

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APPENDICES

Appendix A

Derivations

Derivation of the Posterior Function

$$
\begin{aligned}
&posterior\left(\begin{array}{c}\left\{V_{ijt}^{*}\right\}_{t=t_{ij}^{0},\forall ij}^{t_{ij}^{1}},\{c_{ij}\}_{\forall ij},\{d_{it}\}_{t=t_{i}^{0},\forall i}^{t_{i}^{1}},\{e_{jt}\}_{t=t_{j}^{0},\forall j}^{t_{j}^{1}},\tau,\beta,\delta,\sigma^{2}\\ |\left\{Y_{ijt}\right\}_{t=t_{ij}^{0},\forall ij}^{t_{ij}^{1}},\{z_{ijt}\}_{t=t_{ij}^{0},\forall ij}^{t_{ij}^{1}}\end{array}\right)\\
&\propto prior\left(\tau,\beta,\delta,\sigma^{2}\right)\\
&*\Pr\left(\begin{array}{c}\left\{V_{ijt}^{*}\right\}_{t=t_{ij}^{0},\forall ij}^{t_{ij}^{1}},\{Y_{ijt}\}_{t=t_{ij}^{0},\forall ij}^{t_{ij}^{1}},\{c_{ij}\}_{\forall ij},\{d_{it}\}_{t=t_{i}^{0},\forall i}^{t_{i}^{1}},\{e_{jt}\}_{t=t_{j}^{0},\forall j}^{t_{j}^{1}}\\ |\tau,\beta,\delta,\sigma^{2},\{Y_{ij0}\}_{\forall ij},\{z_{ijt}\}_{t=t_{ij}^{0},\forall ij}^{t_{ij}^{1}}\end{array}\right)\\
&=prior\left(\tau,\beta,\delta,\sigma^{2}\right)\\
&*\Pr\left(\begin{array}{c}\left\{V_{ijt}^{*}\right\}_{t=t_{ij}^{0},\forall ij}^{t_{ij}^{1}},\{Y_{ijt}\}_{t=t_{ij}^{0},\forall ij}^{t_{ij}^{1}}\\ |\{c_{ij}\}_{\forall ij},\{d_{it}\}_{t=t_{i}^{0},\forall i}^{t_{i}^{1}},\{e_{jt}\}_{t=t_{j}^{0},\forall j}^{t_{j}^{1}},\tau,\beta,\delta,\sigma^{2},\{Y_{ij0}\}_{\forall ij},\{z_{ijt}\}_{t=t_{ij}^{0},\forall ij}^{t_{ij}^{1}}\end{array}\right)\\
&*\Pr\left(\{c_{ij}\}_{\forall ij},\{d_{it}\}_{t=t_{i}^{0},\forall i}^{t_{i}^{1}},\{e_{jt}\}_{t=t_{j}^{0},\forall j}^{t_{j}^{1}}|\tau,\beta,\delta,\sigma^{2},\{Y_{ij0}\}_{\forall ij},\{z_{ijt}\}_{t=t_{ij}^{0},\forall ij}^{t_{ij}^{1}}\right)\\
&=prior\left(\tau,\beta,\delta,\sigma^{2}\right)\\
&*\prod_{i=1}^{I}\prod_{j=1}^{J_{i}}\prod_{t=t_{ij}^{0}}^{t_{ij}^{1}}\Pr\left(V_{ijt}^{*},Y_{ijt}|Y_{ijt-1},c_{ij},d_{it},e_{jt},\tau,\beta,\sigma_{\varepsilon}^{2},z_{ijt}\right)\\
&*\prod_{i=1}^{I}\prod_{j=1}^{J_{i}}\Pr\left(c_{ij}|\delta_{c},\sigma_{\alpha}^{2}\right)*\prod_{i=1}^{I}\prod_{t=t_{i}^{0}}^{t_{i}^{1}}\Pr\left(d_{it}|\delta_{d},\sigma_{\zeta}^{2}\right)*\prod_{j=1}^{J}\prod_{t=t_{j}^{0}}^{t_{j}^{1}}\Pr\left(e_{jt}|\delta_{e},\sigma_{v}^{2}\right)
\end{aligned}
$$

$$= prior\left(\tau,\beta,\delta,\sigma^2\right)$$
$$*\prod_{i=1}^{I}\prod_{j=1}^{J_i}\prod_{t=t_{ij}^0}^{t_{ij}^1}\Pr\left(Y_{ijt}|V_{ijt}^*,\tau\right)\Pr\left(V_{ijt}^*|Y_{ijt-1},c_{ij},d_{it},e_{jt},\beta,\sigma_\varepsilon^2,z_{ijt}\right)$$
$$*\prod_{i=1}^{I}\prod_{j=1}^{J_i}\Pr\left(c_{ij}|\delta_c,\sigma_\alpha^2\right)*\prod_{i=1}^{I}\prod_{t=t_i^0}^{t_i^1}\Pr\left(d_{it}|\delta_d,\sigma_\zeta^2\right)*\prod_{j=1}^{J}\prod_{t=t_j^0}^{t_j^1}\Pr\left(e_{jt}|\delta_e,\sigma_v^2\right)$$
$$= prior\left(\tau,\beta,\delta,\sigma^2\right)$$
$$*\prod_{i=1}^{I}\prod_{j=1}^{J_i}\prod_{t=t_{ij}^0}^{t_{ij}^1}\left\{\begin{array}{c}\left[I(V_{ijt}^*>\log(\tau))I(Y_{ijt}=\exp(V_{ijt}^*)-\tau)+I(V_{ijt}^*\leq\log(\tau))I(Y_{ijt}=0)\right]\\ \times\frac{1}{\sqrt{2\pi\sigma_\varepsilon^2}}\exp\left[-\frac{1}{2\sigma_\varepsilon^2}(V_{ijt}^*-w_{ijt}\beta-c_{ij}-d_{it}-e_{jt})^2\right]\end{array}\right\}$$
$$*\prod_{i=1}^{I}\prod_{j=1}^{J_i}\left\{\frac{1}{\sqrt{2\pi\sigma_\alpha^2}}\exp\left[-\frac{1}{2\sigma_\alpha^2}(c_{ij}-\delta_{c1}Y_{ij0}-\delta_{c2}\overline{z}_{ij})^2\right]\right\}$$
$$*\prod_{i=1}^{I}\prod_{t=t_i^0}^{t_i^1}\left\{\frac{1}{\sqrt{2\pi\sigma_\zeta^2}}\exp\left[-\frac{1}{2\sigma_\zeta^2}(d_{it}-\delta_d\overline{z}_{it})^2\right]\right\}$$
$$*\prod_{j=1}^{J}\prod_{t=t_j^0}^{t_j^1}\left\{\frac{1}{\sqrt{2\pi\sigma_v^2}}\exp\left[-\frac{1}{2\sigma_v^2}(e_{jt}-\delta_e\overline{z}_{jt})^2\right]\right\}$$

Derivation of $p(\tau|\{c_{ij}\}_{\forall ij},\{d_{it}\}_{t=t_i^0,\forall i}^{t_i^1},\{e_{jt}\}_{t=t_j^0,\forall j}^{t_j^1},\beta,\sigma_\varepsilon^2,\{Y_{ijt}\}_{\forall ijt},\{z_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1})$

$$
\begin{aligned}
&p(\tau|\{c_{ij}\}_{\forall ij},\{d_{it}\}_{t=t_i^0,\forall i}^{t_i^1},\{e_{jt}\}_{t=t_j^0,\forall j}^{t_j^1},\beta,\sigma_\varepsilon^2,\{Y_{ijt}\}_{\forall ijt},\{z_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1})\\
&=\int p\left(\tau,\left\{V_{ijt}^*\right\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}|\{c_{ij}\}_{\forall ij},\{d_{it}\}_{t=t_i^0,\forall i}^{t_i^1},\{e_{jt}\}_{t=t_j^0,\forall j}^{t_j^1},\beta,\sigma_\varepsilon^2,\{Y_{ijt}\}_{\forall ijt},\{z_{ijt}\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}\right)\\
&d\left\{V_{ijt}^*\right\}_{t=t_{ij}^0,\forall ij}^{t_{ij}^1}\\
&=\prod_{i=1}^{I}\prod_{j=1}^{J_i}\prod_{t=t_{ij}^0}^{t_{ij}^1}\int\left\{\begin{array}{c}\left\{\begin{array}{c}I\left[V_{ijt}^*>\log(\tau)\right]I\left[Y_{ijt}=\exp(V_{ijt}^*)-\tau\right]\\+I\left[V_{ijt}^*\le\log(\tau)\right]I(Y_{ijt}=0)\end{array}\right\}\\*\frac{1}{\sqrt{2\pi\sigma_\varepsilon^2}}\exp\left[-\frac{1}{2\sigma_\varepsilon^2}(V_{ijt}^*-w_{ijt}\beta-c_{ij}-d_{it}-e_{jt})^2\right]\end{array}\right\}dV_{ijt}^*\\
&*prior(\tau),
\end{aligned}
\tag{A.1}
$$

where the second equality follows from (1.4). When, $Y_{ijt}>0$,

$$
\begin{aligned}
&\int\left\{\begin{array}{c}\left\{I\left[V_{ijt}^*>\log(\tau)\right]I\left[Y_{ijt}=\exp(V_{ijt}^*)-\tau\right]+I\left[V_{ijt}^*\le\log(\tau)\right]I(Y_{ijt}=0)\right\}\\*\frac{1}{\sqrt{2\pi\sigma_\varepsilon^2}}\exp\left[-\frac{1}{2\sigma_\varepsilon^2}(V_{ijt}^*-w_{ijt}\beta-c_{ij}-d_{it}-e_{jt})^2\right]\end{array}\right\}dV_{ijt}^*\\
&=\int\left\{\begin{array}{c}I\left[V_{ijt}^*>\log(\tau)\right]I\left[Y_{ijt}=\exp(V_{ijt}^*)-\tau\right]\\*\frac{1}{\sqrt{2\pi\sigma_\varepsilon^2}}\exp\left[-\frac{1}{2\sigma_\varepsilon^2}(V_{ijt}^*-w_{ijt}\beta-c_{ij}-d_{it}-e_{jt})^2\right]\end{array}\right\}dV_{ijt}^*\\
&=\frac{1}{(Y_{ijt}+\tau)}\frac{1}{\sqrt{2\pi\sigma_\varepsilon^2}}\exp\left\{-\frac{1}{2\sigma_\varepsilon^2}\left[\log\left(Y_{ijt}+\tau\right)-w_{ijt}\beta-c_{ij}-d_{it}-e_{jt}\right]^2\right\}\\
&\propto\frac{1}{(Y_{ijt}+\tau)}\exp\left\{-\frac{1}{2\sigma_\varepsilon^2}\left[\log\left(Y_{ijt}+\tau\right)-w_{ijt}\beta-c_{ij}-d_{it}-e_{jt}\right]^2\right\}.
\end{aligned}
\tag{A.2}
$$

When $Y_{ijt}=0$,

$$
\begin{aligned}
&\int\left\{\begin{array}{c}\left\{I\left[V_{ijt}^*>\log(\tau)\right]I\left[Y_{ijt}=\exp(V_{ijt}^*)-\tau\right]+I\left[V_{ijt}^*\le\log(\tau)\right]I(Y_{ijt}=0)\right\}\\*\frac{1}{\sqrt{2\pi\sigma_\varepsilon^2}}\exp\left[-\frac{1}{2\sigma_\varepsilon^2}(V_{ijt}^*-w_{ijt}\beta-c_{ij}-d_{it}-e_{jt})^2\right]\end{array}\right\}dV_{ijt}^*\\
&=\int\left\{I\left[V_{ijt}^*\le\log(\tau)\right]\frac{1}{\sqrt{2\pi\sigma_\varepsilon^2}}\exp\left[-\frac{1}{2\sigma_\varepsilon^2}(V_{ijt}^*-w_{ijt}\beta-c_{ij}-d_{it}-e_{jt})^2\right]\right\}dV_{ijt}^*\\
&=\int_{-\infty}^{\log(\tau)}\frac{1}{\sqrt{2\pi\sigma_\varepsilon^2}}\exp\left[-\frac{1}{2\sigma_\varepsilon^2}(V_{ijt}^*-w_{ijt}\beta-c_{ij}-d_{it}-e_{jt})^2\right]dV_{ijt}^*\\
&=\Phi\left(\frac{\log(\tau)-w_{ijt}\beta-c_{ij}-d_{it}-e_{jt}}{\sigma_\varepsilon}\right).
\end{aligned}
\tag{A.3}
$$

Plugging (A.2) and (A.3) into (A.1) gives (1.5).

Derivation of $E\left[Y_{ijt}|w_{ijt}, c_{ij}, d_{it}, e_{jt}\right]$

$$
\begin{aligned}
E\left[Y_{ijt}|w_{ijt}, c_{ij}, d_{it}, e_{jt}\right] &= \Pr(Y_{ijt}=0|w_{ijt}, c_{ij}, d_{it}, e_{jt}) * E(Y_{ijt}|Y_{ijt}=0, w_{ijt}, c_{ij}, d_{it}, e_{jt}) \\
+\Pr(Y_{ijt} &> 0|w_{ijt}, c_{ij}, d_{it}, e_{jt}) * E(Y_{ijt}|Y_{ijt}>0, w_{ijt}, c_{ij}, d_{it}, e_{jt}) \\
&= \Pr(Y_{ijt}>0|w_{ijt}, c_{ij}, d_{it}, e_{jt}) * E\left(Y^*_{ijt}|Y^*_{ijt}>0, w_{ijt}, c_{ij}, d_{it}, e_{jt}\right) \\
&= \Pr\left(Y^*_{ijt}>0|w_{ijt}, c_{ij}, d_{it}, e_{jt}\right) * E\left(Y^*_{ijt}|Y^*_{ijt}>0, w_{ijt}, c_{ij}, d_{it}, e_{jt}\right) \\
&= \Pr\left[\log\left(Y^*_{ijt}+\tau\right) > \log\tau|w_{ijt}, c_{ij}, d_{it}, e_{jt}\right] \\
&\quad *E\left(Y^*_{ijt}|Y^*_{ijt}>0, w_{ijt}, c_{ij}, d_{it}, e_{jt}\right) \\
&= \Pr\left(\frac{A_{ijt}}{\sigma_\varepsilon} + \frac{\varepsilon_{ijt}}{\sigma_\varepsilon} > \frac{\log\tau}{\sigma_\varepsilon}|w_{ijt}, c_{ij}, d_{it}, e_{jt}\right) \\
&\quad *E\left(Y^*_{ijt}|Y^*_{ijt}>0, w_{ijt}, c_{ij}, d_{it}, e_{jt}\right) \\
\text{where } A_{ijt} &\equiv \log\left(Y_{ijt-1}+\tau\right)\rho + z_{ijt}\theta + c_{ij} + d_{it} + e_{jt} \\
&= \Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right) * E\left(Y^*_{ijt}|Y^*_{ijt}>0, w_{ijt}, c_{ij}, d_{it}, e_{jt}\right) \\
&= \Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right) * \left[E\left(Y^*_{ijt}+\tau|Y^*_{ijt}>0, w_{ijt}, c_{ij}, d_{it}, e_{jt}\right) - \tau\right] \\
&= \Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right) * \left[E\left(Y^*_{ijt}+\tau|Y^*_{ijt}+\tau>\tau, w_{ijt}, c_{ij}, d_{it}, e_{jt}\right) - \tau\right] \\
&= \Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right) * \left[E\left(\begin{array}{c} Y^*_{ijt}+\tau|\log\left(Y^*_{ijt}+\tau\right) \\ >\log\tau, w_{ijt}, c_{ij}, d_{it}, e_{jt}\end{array}\right) - \tau\right] \\
&= \Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right) * \left[\exp\left(A_{ijt}+\frac{\sigma^2_\varepsilon}{2}\right) * \frac{\Phi\left(\sigma_\varepsilon - \frac{\log\tau-A_{ijt}}{\sigma_\varepsilon}\right)}{\Phi\left(-\frac{\log\tau-A_{ijt}}{\sigma_\varepsilon}\right)} - \tau\right] \\
&= \Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right) * \left[\exp\left(A_{ijt}+\frac{\sigma^2_\varepsilon}{2}\right) * \frac{\Phi\left(\sigma_\varepsilon + \frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)}{\Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)} - \tau\right],
\end{aligned}
$$

where the second last equality follows from one of the properties of conditional expectation for log-normal density (see page 867 of Greene 2008).

Derivation of $\frac{\partial E[Y_{ijt}|w_{ijt},c_{ij},d_{it},e_{jt}]}{\partial Y_{ijt-1}}$

$$\frac{\partial E[Y_{ijt}|w_{ijt},c_{ij},d_{it},e_{jt}]}{\partial Y_{ijt-1}} = \phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{\rho}{\sigma_\varepsilon(Y_{ijt-1}+\tau)} * \left[\begin{array}{c} \exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right) * \frac{\Phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)}{\Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)} \\ -\tau \end{array}\right]$$

$$+\Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right) * \left[\begin{array}{c} \exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right)\frac{\rho}{(Y_{ijt-1}+\tau)} * \frac{\Phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)}{\Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)} \\ +\exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right) * \frac{\phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{\rho}{\sigma_\varepsilon(Y_{ijt-1}+\tau)}}{\Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)} \\ -\exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right) * \frac{\Phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)}{\Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)^2} * \phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{\rho}{\sigma_\varepsilon(Y_{ijt-1}+\tau)} \end{array}\right]$$

$$= \phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{\rho}{\sigma_\varepsilon(Y_{ijt-1}+\tau)}\exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right)\frac{\Phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)}{\Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)}$$
$$-\phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{\rho}{\sigma_\varepsilon(Y_{ijt-1}+\tau)}\tau$$
$$+\exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right)\frac{\rho}{(Y_{ijt-1}+\tau)}\Phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)$$
$$+\exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right)\phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{\rho}{\sigma_\varepsilon(Y_{ijt-1}+\tau)}$$
$$-\phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right)\frac{\Phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)}{\Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)}\frac{\rho}{\sigma_\varepsilon(Y_{ijt-1}+\tau)}$$

$$= -\phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{\rho}{\sigma_\varepsilon(Y_{ijt-1}+\tau)}\tau$$
$$+\exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right)\frac{\rho}{(Y_{ijt-1}+\tau)}\left[\Phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)+\phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{1}{\sigma_\varepsilon}\right]$$

$$= \left\{\begin{array}{c} -\phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{\tau}{\sigma_\varepsilon} \\ +\exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right)\left[\begin{array}{c} \Phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right) \\ +\phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{1}{\sigma_\varepsilon} \end{array}\right] \end{array}\right\}\frac{1}{(Y_{ijt-1}+\tau)} * \rho$$

Derivation of $\frac{\partial E[Y_{ijt}|w_{ijt},c_{ij},d_{it},e_{jt}]}{\partial z_{ijt,k}}$

$$\frac{\partial E[Y_{ijt}|w_{ijt},c_{ij},d_{it},e_{jt}]}{\partial z_{ijt,k}} = \phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{\theta_k}{\sigma_\varepsilon} * \left[\exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right) * \frac{\Phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)}{\Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)} - \tau\right]$$

$$+\Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right) * \left[\begin{array}{c} \exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right)\theta_k * \frac{\Phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)}{\Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)} \\ +\exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right) * \frac{\phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{\theta_k}{\sigma_\varepsilon}}{\Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)} \\ -\exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right) * \frac{\Phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)}{\Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)^2} * \phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{\theta_k}{\sigma_\varepsilon} \end{array}\right]$$

$$= \phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{\theta_k}{\sigma_\varepsilon} * \exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right) * \frac{\Phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)}{\Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)} - \phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{\theta_k}{\sigma_\varepsilon}\tau$$
$$+\exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right) * \Phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\theta_k$$
$$+\exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right) * \phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{\theta_k}{\sigma_\varepsilon}$$
$$-\phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right) * \exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right) * \frac{\Phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)}{\Phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)}\frac{\theta_k}{\sigma_\varepsilon}$$

$$= -\phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{\theta_k}{\sigma_\varepsilon}\tau + \exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right)\left[\begin{array}{c} \Phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\theta_k \\ +\phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{\theta_k}{\sigma_\varepsilon} \end{array}\right]$$

$$= \left\{\begin{array}{c} -\phi\left(\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{\tau}{\sigma_\varepsilon} \\ +\exp\left(A_{ijt}+\frac{\sigma_\varepsilon^2}{2}\right)\left[\Phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)+\phi\left(\sigma_\varepsilon+\frac{A_{ijt}-\log\tau}{\sigma_\varepsilon}\right)\frac{1}{\sigma_\varepsilon}\right] \end{array}\right\} * \theta_k$$

Appendix B

The Computational Problem with an Alternative Specification

For illustration purpose, suppose $t_{ij}^0 = 1$ and $t_{ij}^1 = 3$ and focus on the country pair ij. I use $\log(Y_{ijt-1}^* + \tau)$ instead of $\log(Y_{ijt-1} + \tau)$ as the lagged dependent variable and I redefine w_{ijt} as $w_{ijt} = \left(z_{ijt}',\ \log(Y_{ijt-1}^* + \tau)\right)'$. Then, (A.1) becomes,

$$
\begin{aligned}
& p(\tau | c_{ij}, \{d_{it}\}_{t=t_i^0}^{t_i^1}, \{e_{jt}\}_{t=t_j^0}^{t_j^1}, \beta, \sigma_\varepsilon^2, \{Y_{ijt}\}_{t=t_{ij}^0}^{t_{ij}^1}, \{z_{ijt}\}_{t=t_{ij}^0}^{t_{ij}^1}) \\
& = \int p(\tau, \left\{V_{ijt}^*\right\}_{t=t_{ij}^0}^{t_{ij}^1} | c_{ij}, \{d_{it}\}_{t=t_i^0}^{t_i^1}, \{e_{jt}\}_{t=t_j^0}^{t_j^1}, \beta, \sigma_\varepsilon^2, \{Y_{ijt}\}_{t=t_{ij}^0}^{t_{ij}^1}, \{z_{ijt}\}_{t=t_{ij}^0}^{t_{ij}^1}) d\left\{V_{ijt}^*\right\}_{t=t_{ij}^0}^{t_{ij}^1} \\
& = \int\int\int \prod_{t=1}^{3} \left\{ \begin{array}{c} \left\{ I\left[V_{ijt}^* > \log(\tau)\right] I\left[Y_{ijt} = \exp(V_{ijt}^*) - \tau\right] + I\left[V_{ijt}^* \leq \log(\tau)\right] I(Y_{ijt} = 0) \right\} \\ * \frac{1}{\sqrt{2\pi\sigma_\varepsilon^2}} \exp\left[-\frac{1}{2\sigma_\varepsilon^2} (V_{ijt}^* - w_{ijt}\beta - c_{ij} - d_{it} - e_{jt})^2 \right] \end{array} \right\} \\
& dV_{ij1}^* dV_{ij2}^* dV_{ij3}^* \\
& = \int\int\int \prod_{t=1}^{3} \left\{ \begin{array}{c} \left\{ I\left[V_{ijt}^* > \log(\tau)\right] I\left[Y_{ijt} = \exp(V_{ijt}^*) - \tau\right] + I\left[V_{ijt}^* \leq \log(\tau)\right] I(Y_{ijt} = 0) \right\} \\ * \frac{1}{\sqrt{2\pi\sigma_\varepsilon^2}} \exp\left[-\frac{1}{2\sigma_\varepsilon^2} (V_{ijt}^* - V_{ijt-1}^*\rho - z_{ijt}\theta - c_{ij} - d_{it} - e_{jt})^2 \right] \end{array} \right\} \\
& dV_{ij1}^* dV_{ij2}^* dV_{ij3}^*
\end{aligned}
\tag{B.1}
$$

$$= \int\int\int \left\{ \begin{array}{c} \left\{ I\left[V^*_{ij3} > \log(\tau)\right] I\left[Y_{ij3} = \exp(V^*_{ij3}) - \tau\right] + I\left[V^*_{ij3} \leq \log(\tau)\right] I(Y_{ij3} = 0) \right\} \\ * \frac{1}{\sqrt{2\pi\sigma^2_\varepsilon}} \exp\left[-\frac{1}{2\sigma^2_\varepsilon} (V^*_{ij3} - V^*_{ij2}\rho - z_{ij3}\theta - c_{ij} - d_{i3} - e_{j3})^2 \right] \\ * \left\{ I\left[V^*_{ij2} > \log(\tau)\right] I\left[Y_{ij2} = \exp(V^*_{ij2}) - \tau\right] + I\left[V^*_{ij2} \leq \log(\tau)\right] I(Y_{ij2} = 0) \right\} \\ * \frac{1}{\sqrt{2\pi\sigma^2_\varepsilon}} \exp\left[-\frac{1}{2\sigma^2_\varepsilon} (V^*_{ij2} - V^*_{ij1}\rho - z_{ij2}\theta - c_{ij} - d_{i2} - e_{j2})^2 \right] \\ * \left\{ I\left[V^*_{ij1} > \log(\tau)\right] I\left[Y_{ij1} = \exp(V^*_{ij1}) - \tau\right] + I\left[V^*_{ij1} \leq \log(\tau)\right] I(Y_{ij1} = 0) \right\} \\ * \frac{1}{\sqrt{2\pi\sigma^2_\varepsilon}} \exp\left[-\frac{1}{2\sigma^2_\varepsilon} (V^*_{ij1} - V^*_{ij0}\rho - z_{ij1}\theta - c_{ij} - d_{i1} - e_{j1})^2 \right] \end{array} \right\}$$
$$dV^*_{ij1} dV^*_{ij2} dV^*_{ij3}$$

In (B.1), I need to integrate over V^*_{ij1}, V^*_{ij2} and V^*_{ij3} to get the posterior conditional distribution of τ. In the case there are 3 time periods, there are $2^3 = 8$ cases to consider. For example, for the case $Y_{ij3} > 0$, $Y_{ij2} > 0$ and $Y_{ij1} > 0$, the multiple integral becomes

$$\begin{array}{l} \frac{1}{Y_{ij3}+\tau} \frac{1}{\sqrt{2\pi\sigma^2_\varepsilon}} \exp\left[-\frac{1}{2\sigma^2_\varepsilon} (\log(Y_{ij3} + \tau) - \log(Y_{ij2} + \tau)\rho - z_{ij3}\theta - c_{ij} - d_{i3} - e_{j3})^2 \right] \\ * \frac{1}{Y_{ij2}+\tau} \frac{1}{\sqrt{2\pi\sigma^2_\varepsilon}} \exp\left[-\frac{1}{2\sigma^2_\varepsilon} (\log(Y_{ij2} + \tau) - \log(Y_{ij1} + \tau)\rho - z_{ij2}\theta - c_{ij} - d_{i2} - e_{j2})^2 \right] \\ * \frac{1}{Y_{ij2}+\tau} \frac{1}{\sqrt{2\pi\sigma^2_\varepsilon}} \exp\left[-\frac{1}{2\sigma^2_\varepsilon} (\log(Y_{ij1} + \tau) - V^*_{ij0}\rho - z_{ij1}\theta - c_{ij} - d_{i1} - e_{j1})^2 \right]. \end{array}$$

For another example, for the case $Y_{ij3} = 0$, $Y_{ij2} = 0$ and $Y_{ij1} = 0$, the multiple integral becomes

$$\begin{array}{l} \int_{-\infty}^{\log(\tau)} \int_{-\infty}^{\log(\tau)} \int_{-\infty}^{\log(\tau)} \left\{ \begin{array}{c} \frac{1}{\sqrt{2\pi\sigma^2_\varepsilon}} \exp\left[-\frac{1}{2\sigma^2_\varepsilon} (V^*_{ij3} - V^*_{ij2}\rho - z_{ij3}\theta - c_{ij} - d_{i3} - e_{j3})^2 \right] \\ * \frac{1}{\sqrt{2\pi\sigma^2_\varepsilon}} \exp\left[-\frac{1}{2\sigma^2_\varepsilon} (V^*_{ij2} - V^*_{ij1}\rho - z_{ij2}\theta - c_{ij} - d_{i2} - e_{j2})^2 \right] \\ * \frac{1}{\sqrt{2\pi\sigma^2_\varepsilon}} \exp\left[-\frac{1}{2\sigma^2_\varepsilon} (V^*_{ij1} - V^*_{ij0}\rho - z_{ij1}\theta - c_{ij} - d_{i1} - e_{j1})^2 \right] \end{array} \right\} \\ dV^*_{ij1} dV^*_{ij2} dV^*_{ij3} \\ = \int_{-\infty}^{\log(\tau)} \int_{-\infty}^{\log(\tau)} \Phi\left(\frac{\log(\tau) - V^*_{ij2}\rho - z_{ij3}\theta - c_{ij} - d_{i3} - e_{j3}}{\sigma_\varepsilon} \right) \\ * \frac{1}{\sqrt{2\pi\sigma^2_\varepsilon}} \exp\left[-\frac{1}{2\sigma^2_\varepsilon} (V^*_{ij2} - V^*_{ij1}\rho - z_{ij2}\theta - c_{ij} - d_{i2} - e_{j2})^2 \right] \\ * \frac{1}{\sqrt{2\pi\sigma^2_\varepsilon}} \exp\left[-\frac{1}{2\sigma^2_\varepsilon} (V^*_{ij1} - V^*_{ij0}\rho - z_{ij1}\theta - c_{ij} - d_{i1} - e_{j1})^2 \right] \\ dV^*_{ij2} dV^*_{ij1} \end{array}$$

which is a two-dimensional integral. In general, when there are $t^1_{ij} - t^0_{ij}$ periods in the data for country pair ij, I need to consider $2^{t^1_{ij} - t^0_{ij}}$ cases and I need to compute integrals up to $t^1_{ij} - t^0_{ij} - 1$ dimensions. This makes the computation quite difficult, if not possible, to implement.

Appendix C

List of Countries

High Income Country[1] (38 countries)

Australia (OECD[2]), Austria (OECD; 2008-2009[3]), Belgium (OECD; 2008-2009), Canada (OECD), Croatia, Chile (OECD), Czech Republic (OECD), Denmark (OECD; 2008-2009), Estonia (OECD), Finland (OECD), France (OECD; 2008-2009), Germany (OECD; 2008-2009), Greece (OECD; 2008-2009), Hong Kong, Iceland (OECD; 2008-2009), Ireland (OECD; 2008-2009), Israel (OECD), Italy (OECD; 2008-2009), Japan (OECD), Korea (OECD), Kuwait, Luxembourg (OECD; 2008-2009), Netherlands (OECD; 2008-2009), New Zealand (OECD), Norway (OECD), Poland (OECD), Portugal (OECD; 2008-2009), Russia (2008-2009), Saudi Arabia, Singapore, Slovak Republic (OECD), Slovenia (OECD; 2008-2009), Spain (OECD; 2008-2009), Sweden (OECD; 2008-2009), Switzerland (OECD; 2008-2009), United Arab Emirates, United Kingdom (OECD; 2007-2009), United States (OECD; 2007-2009)

Non-High Income Country (22 countries)

Argentina, Bulgaria, Brazil, China, Colombia, Egypt, Hungary (OECD; 2008-2009), India, Indonesia, Iran, Malaysia, Mexico (OECD), Morocco, Nigeria (2009), Pakistan, Philippines, Thailand, Turkey (OECD), Ukraine (2008-2009), Venezuela, Vietnam, South Africa

[1] It is based on the World Bank's income classification (January 2015).
[2] 34 OECD countries
[3] Banking Crises Dates