An Application of the Gravity Model to International Trade in Narcotics

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Summary

The transnational traffic of narcotics has had undeniable impacts on international development, for instance, stagnant economic growth in Myanmar (Chin, 2009), unsustainable agricultural practices in Yemen (Robins, 2016), and human security threats in Columbia (Thoumi, 2013). Furthermore, globalization is a catalyst for the transnational narcotics traffic (Robins, 2016; Aas, 2007; Kelly, Maghan & Serio, 2005). Several qualitative studies exist on the transnational narcotics traffic, yet few quantitative studies examine the issue. There is thus an opportunity for novel quantitative studies on the general question: "what are the main economic factors that influence the transnational traffic of narcotics between countries?" This study looked at the specific question: "are distance and economic size correlated with the volume of narcotics traffic between countries?"

This study chose the gravity model as it centres on bilateral trade (Tinbergen, 1962), accounts for trade barriers (Kalirajan, 2008) and is empirically robust (Anderson 2011). This study defined a basic functional gravity model relating a proxy of the narcotics traffic to distance and economic size. Four augmented functional gravity models were also advanced to address omitted variable bias. The research was limited conceptually to cross sectional and pooled time series data. In addition, the data was also limited practically to a convenience sample of secondary data drawn from: the United Nations Office on Drugs and Crime's (UNODC) (2016a) Individual Drug Seizures (IDS); the World Bank's (2016) World Development Indicators; and the CEPII's GeoDist (2016) datasets. This study used a novel "dosage" approach to unit standardization to overcome the challenge posed by the many measures and forms of narcotics. The study

used the Poisson pseudo maximum likelihood (PPML) estimator as its estimations of the gravity model are consistent (Gourieroux et al., 1984), allow heteroscedasticity (Silva & Tenreyro, 2006) and avoid back transformation bias (Cox et al., 2008).

The evidence analyzed in this study seem to indicate that the gravity model may not be applicable in its current form to the transnational narcotics traffic among countries that report drug seizures to the UNODC. However, the sampling method and the choice of proxy are likely to influence these findings. Moreover, the low explanatory power of the gravity model for the narcotics traffic, reflected in the values of the pseudo-R-squared coefficient of determination, indicates that other factors are at play. For instance, authors such as Asad and Harris (2003) and Thoumi (2003) argue that institutions could be a key factor in the narcotics traffic. Future empirical research into this topic could build on the theses findings to introduce new proxies and to explore alternate theoretical frameworks.

Chapter 1: Introduction and Significance

1.1 Topic: The Transnational Narcotics Traffic

The international prohibition on the recreational use of psychotropic substances, also known as narcotics or illicit drugs, and the corresponding "war" on drugs has been a popular subject in recent films and television series. This is especially the case for period pieces such as *Narcos* and *American Made*. *Narcos* which Doyle describes as a "brilliant epic about the drug trade" follows the saga of the Medellín and Cali cartels (2017). Whereas, *American Made*, starring Tom Cruise as Barry Seal, takes a look at his questionable dealings in Latin America (Lane, 2017). No matter how entertaining, the transnational narcotics traffic and the "war" on drugs are more than a plot device and have real and tragic present day consequences. For example, the "war" on drugs continues to this day in countries such as the United States and the Philippines. In 2016 alone, American law enforcement arrested approximately 1.5 million individuals for drug-related offences and the current American Attorney General, Jeff Sessions, has vowed to pursue a policy of zero tolerance (Ingraham, 2017). Furthermore, Philippines President Rodrigo Duterte's violent "war" on drugs has reportedly cost the lives of over 1000 individuals, and the independent Commission on Human Rights, mandated to investigate these deaths, has seen its budget cut to 1000 pesos (roughly USD 20) (BBC, 2017). However, policy towards the narcotics traffic is changing as decriminalization and legalization gain momentum. In Portugal, 16 years after the decriminalization of all narcotics, heroin use has fallen from 100,000 individuals to 25,000 individuals (Kristof, 2017). And here in Canada, the federal government is looking to legalize the recreational use of marijuana by July 2018 (Presse canadienne, 2017). The public interest in the narcotics trade, the human tragedy of the "war" on drugs, and the new policy agenda on narcotics has made it imperative to understand fully the economics at play. The following paragraphs will outline a working definition of this study's key concepts, including globalization, international development and the transnational narcotics traffic.

There is no universal definition of globalization and authors often use the term very differently from one another. Canet (2013) notes that when the word globalization was gaining popularity in the 1990s it essentially referred to the expansion of international trade and the creation of a global market. Godinot (2008) for his part defines globalization as a network of interdependence between human beings, their activities, and their political systems on a planetary scale. For the purpose of this study, we will use the relatively narrow interpretation of globalization as a dynamic and ongoing expansion of trade networks and economic activities at a global scale (Canet, 2013). Therefore, we will interpret globalization as the increase in the flows of labour, capital, goods and information across international borders.

Authors such as Rist (2007) have been quite critical of the international development concept, particularly the blind faith in its goals and the dubious means used to achieve them. Thus, Rist (2007) proposed an interpretation of development that tries to dispel the mythology surrounding the concept. Rist's (2007) definition is that development is a set of apparently contradictory practices to assure social reproduction, which transforms and destroys the natural and social world to generate the necessary growth of goods and services to meet the demand through trade. However, Sen (2000) sees two general interpretations of international development, the one being a hard road to a set of key objectives, and the second being a vast field for the improvement of comprehensive goals. For the purpose of this study, the following working definition is advanced: development is the process of achieving certain specific and general social and economic goals to better the human condition.

This study will define the transnational narcotics traffic as the trade flow of illicit drugs across national borders. The market driving the production, traffic and consumption of narcotics is substantial.

In 2013, according to the United Nations (2015), there was an estimated 246 million illicit drug users worldwide. This represents “1 out of 20 people between the ages of 15 and 64 years” (United Nations, 2015, p. ix). Furthermore, according to the United Nations Office on Drug and Crime (UNODC) the value at retail of the global narcotics market is USD 332 billion (United Nations, 2005). However, researchers such as Reuter and Greenfield (2001) believe that the narcotic market (agricultural and synthetic) has a value of USD 20–25 billion comparable to the coffee market. Regardless of the true market size, the transnational narcotics traffic has been increasing in both scope and scale, and has an established link to globalization (Robins, 2016; Singer, 2008; Aas, 2007). This study will look at globalization as a catalyst for the narcotics traffic in greater detail in section 2.1.

1.2 Problem: A Threat and Barrier to Development

The transnational narcotics traffic has negative and tangible impacts on the development of many low and middle-income countries (Robins, 2016; Polet 2013; Chin, 2009; Kelly, Maghan & Serio, 2005; Thoumi, 2003; Mamani-Pocoata, 1996). Authors often describe the impact of this traffic on development as a barrier or a threat to process aimed at achieving social and economic goals. The following section will delve into three examples of the threat posed to development by the traffic of narcotics in low and middle-income countries. Notably, the economic “vicious circle”, sustainability of production and the deterioration of human security.

The United Nations (2015) argues that the cultivation and production of narcotics are the first steps in a so-called “vicious circle” affecting economic development. The logic is that increases in the production of narcotics lead to decreases in the rule of law. Which in turn, negatively impacts the legitimate economy and leads to a reduction in legitimate investments. This chain of events can then lead to a further increase in narcotics production. The realities in Myanmar (Chin, 2009) and Afghanistan (Perl, 2001) do seem to support the idea of a “vicious circle”, where narcotics production starts as an attractive livelihood for poor households but ends as a tool for the capture of wealth by political elites.

The impact of the narcotics traffic on the legitimate economy is a central issue in Chin's (2009) book *The Golden Triangle*, a compelling study of the Wa state, located at the border of Myanmar, Thailand and Laos. Chin (2009) rejects the assumption that organized crime, local militants and corrupt official simply conspire to profit on the narcotics trade. For example, there is little evidence of systemic collusion on the part of Burmese authorities. However, among Wa leaders there is a desire for independence and statehood that requires expensive investments in infrastructure and military power. As they perceive the narcotics trade as any other economic endeavour, the solution was to "tax" production. However, this was a slippery slope with many Wa leaders eventually participating directly in the narcotics trade. The consequence of this is that the line between the Wa state builder and the Wa drug kingpin is irreversibly blurred. In the long term this is likely to harm the emergence of legitimate enterprises and slow the development of the Wa state.

Another example of this vicious cycle is the Afghan story under the Taliban rule in the late 1990s. Even though the Taliban did enact more than one ban on opium, its production remained a key source of financing for their activities. For instance, "although the Taliban reportedly banned opium poppy cultivation in late 1997, opium production in Afghanistan increased through the year 2000, accounting for 72% of the world's illicit opium supply" (Perl, 2001, p. 2). Furthermore, according to the US Department of State's (2001) *International Narcotics Control Strategy Report* the Taliban actively promoted the planting of opium to fund their military efforts. Yet they nearly broke this vicious cycle by credibly enforcing their 2000 ban on opium. This ban led to a 99% reduction in production from 2000 to 2001 (Farrell, 2005). Arguably the most effective drug enforcement effort in recent history, it may have been an effort by then Taliban supreme leader Mullah Omar to legitimize his rule internationally.

The production of narcotics can also have a serious impact on sustainable development and strong examples of this can be seen in Yemen (Robins, 2016) and in Bolivia (Mamani-Pocoata, 1996). In Yemen, the unrestrained production of qat is emerging as a threat to the sustainability of agriculture, whereas in Bolivia the blanket prohibition of coca leaf production is a barrier to traditional sustainable practices. Although, the local contexts diverge considerably, the example of Yemen and Bolivia below both illustrate that the production of narcotics has a significant impact on the sustainable development of low-income countries especially in rural communities.

According to Robins' (2016) case study, qat is a mild stimulant, similar to coffee, that is popular in Yemen were farmers grow and sell large quantities of it. This is problematic, as the production of qat represents a disproportionate share of Yemen's scarce water and land resources. In effect qat has become a monoculture in Yemen depleting its aquifers and replacing its food crops. This poses a serious threat to the country's long-term economic and social fabric, and entrenched qat habits among consumers and powerful lobbies among producers have effectively blocked any solution to the issue.

The anthropologist Mamani-Pocoataco (1996) in his chapter *Les ironies du développement alternatif en Bolivie* stress the traditional place of the coca leaf in Andean culture and its many nutritional and medicinal properties. He is also quite critical of what he perceives as a sweeping false equation of the production of the coca leaf with that of cocaine in Andean localities by the international community. Under the banner of "alternative development" crop substitution policies such as *Agroyungas* have been implemented in Bolivia. However, by ignoring the local importance of the coca leaf these policies have had perverse impacts, further marginalizing these communities and threatening the livelihoods of subsistence farmers.

Human security is a framework that views security from the perspective of the individual and the economic and social challenges that he or she faces (Gregoratti, 2013). Accepting this framework, we see that, although narcotics trafficking does not always threaten conventional state security, it has an undeniable impact on the security of individuals in several middle-income countries. For example, in Mexico (Astorga, 2013) the mobilization of the army in response to violent traffickers has led to human rights abuses and in Columbia (Thoumi, 2013) violent actors in departments were drug trafficking is prevalent have jeopardized the physical safety of individuals.

From December 2006 to September 2012, 47,515 deaths are attributed to clashes between criminal organizations in Mexico (Astorga, 2013). The spectacular use of violence by organized crime and trafficking networks, among other factors, prompted the deployment of the army in Mexico. The massive use of military forces, far from reducing the scope and scale of the violence, has created a climate favourable to corruption and civil rights abuses. This has undermined the legitimacy of Mexican government forces and placed a serious strain on the development of many Mexican states. Authors such as Polet (2013) even argue that the international trade of narcotics is a barrier to democracy in low and middle-income countries.

Columbia has had a history of violence in the 20th century with violent deaths peaking in the 1950s (Thoumi, 2013). However, violent deaths increased again in the 1980s and 1990s, especially in Columbian departments were violent actors, such as drug traffickers, were concentrated. These actors contribute to the increase in violent deaths by bringing both the tools and knowledge to carry out these acts (Thoumi, 2013). This has a devastating impact on the human security of Colombians living in violence stricken departments where the state is unable to guarantee their safety.

1.3 Research Question: Economic Factors of the Narcotics Traffic

Given the established detrimental impact of the narcotics traffic on international development, notably in terms of economic growth, sustainability and human security, it is clear that a development scholar should care about this transnational issue. Simply put, the transnational narcotics traffic has had an undeniable effect on the lives and livelihoods of individuals in low and middle-income countries. The general question then arises: "what are the main economic factors that influence the transnational traffic of narcotics between countries?"

In the interdisciplinary literature, there are many regional and national qualitative studies addressing this question, such as Thoumi's (2003) study of the Andes as well as Robins' (2016) study of the Middle East. However, Thoumi (2003) is quick to decry the lack of statistical studies and models examining the question. In addition, Albertson and Fox (2012) comment on the absence of reliable data on the topic. This may be the case because of the challenges posed to quantitative research by the secretive nature of the narcotics traffic (Kelly et al., 2005). Another interesting reason this may be the case, is that research into the narcotics traffic has limited itself to interviews with members of trafficking networks and the intelligence community (Robins, 2016). However, the emergence of open source data on the topic, such as the UNODC's (2016) IDS dataset, creates an opportunity to add novel quantitative studies to an already rich qualitative literature.

There is both a need and an opportunity for novel empirical analysis of the narcotics traffic. Therefore, the motivation for this study was simultaneously to further our understanding of this important issue and contribute to the emerging quantitative literature on the topic. Nested within the studies general question is the specific research question, "are distance and economic size correlated with the volume of narcotics traffic between countries?" This study hypothesizes that, for countries where the narcotics traffic in present, distance and economic size are in fact correlated with the volume of narcotics traffic between countries.

Chapter 2: Review of Literature

2.1 State of the Literature: Economics and Global Studies

This study looked at the interdisciplinary literature tackling the factors that influence the volume of the narcotics traffic between countries, and found compelling texts in both the field of economics and global studies. For the most part, these texts were empirical, with the exception of Umprimny (1996), and relied on qualitative evidence (Robins, 2016; Kelly et al., 2005; Asad & Harris, 2003; Thoumi; 2003) as well as historical evidence (Singer, 2008). In addition, Albertson and Fox (2012) and Aas (2007) supplemented their arguments with some quantitative evidence. The following section will examine in some depth the existing research into the underlying factors of the transnational narcotics traffic.

When it comes to the economic perspective on the question, "what are the main economic factors that influence the transnational traffic of narcotics between countries?" there is a wealth of hypotheses. That said, this study will categorize these hypotheses into two general camps, the "market" and "institution" perspectives. On the "market" perspective side Albertson and Fox (2012) and Umprimny (1996), argue that, although the narcotics traffic exhibits some unique characteristics, it is ultimately a market that falls within the laws of supply and demand. On the "institution" side Asad and Harris (2003) and Thoumi (2003), posit that the strength of institutions, such as the rule of law, plays a large role in the narcotics traffic. Although, the "market" and "institution" perspectives diverge they do not violate the necessary assumptions for the Anderson and Van-Wincoop (2003) derivation of the gravity model used by this study, notably, imperfect competition and product differentiation.

Albertson and Fox (2012) examine the economics of illicit drugs in their book *Crime and Economics,* and they argue that supply and demand forces, similar to those at play for coffee, drive the markets for narcotics. That said, they also caution against blindly applying economic principles to the narcotics traffic as it has been shown to operate in a counterintuitive fashion. For example, non-monetary cost borne by the supply side of the narcotics traffic may account for over 50% of the retail value. The authors support their case by citing recent studies into narcotics such as Reuter and Greenfield (2001).

In the anthology *Drogues et narco-trafic*, Umprimny (1996) in his chapter *Le Narco-trafic comme forme particulière de l'accumulation mercantile* makes a theoretical argument that the two central aspects of the narcotics traffic are that it is both "illegal" and "commercial". By "commercial" he means that, contrary to other crimes such as kidnapping, the narcotics traffic creates wealth, uses minimal coercion and adheres to the laws of the market. Moreover, by "illegal" he implies that the prohibition on drugs creates an unstable market environment of imperfect information and high risk. In other words, the author sees the narcotics traffic as a global market faced with a high tax burden and widespread non-tariff barriers to trade.

In their study *The Politics and Economics of Drug Production on the Pakistan-Afghanistan Border*, Asad and Harris (2003) seek to uncover the extent of historical, economic, geographical and political factors in the region's narcotics production. This study relied on three rounds of interviews conducted in the Northwest Frontier Province of Pakistan with various levels of society. What they find is that poor economic prospects, political turmoil and cultural networks have facilitated the production of narcotics in Pakistan. Notably, that the drug-producing areas share similar economic attributes such as al remoteness, economic vulnerability, prevalent subsistence farming, large family sizes, high unemployment, and widespread poverty.

Thoumi (2003) in *Illegal Drugs, Economy, Society in the Andes* paints a broad picture of the region's relationship with narcotics. The author raises the far-reaching and fundamental question "why do some countries produce illegal drugs and why others not do so" (p. 48). What he believes are the answers most commonly found in the literature, are poverty, corruption, inequality, and economic shocks. Yet, he argues that none of these answers are entirely convincing, proposing instead that competitive advantages stemming from particular social and institutional arrangements are responsible for the production of narcotics.

When looking at the global studies writing on the question, “what are the main economic factors that influence the transnational traffic of narcotics between countries?” the recurring theme is globalization. Notably, the idea that the forces driving the increase in the flow of goods, services, capital and information between nation states are simultaneously increasing the volume of the narcotics traffic. Examples range from the post-Cold War liberalization of markets (Kelly et al., 2005) to the rise of transnational criminal networks (Allen, 2005). In this context, the gravity model remains appealing because of its inclusion of economic size and distance. However, these perspectives tackle the question on a longer time frame than this study can examine due to the availability of data.

Motivated by the lack of empirical writing on narcotics in North Africa and the Arabian Peninsula, Robins (2016) wrote *Middle East Drugs Bazaar*, a series of ten case studies on producing, transit and consuming countries. Unlike previous studies, the author relied on open source information, such as UNODC data, to support his conclusions. When it comes to the trafficking of narcotics in the Middle East there is a long-term trend away from regional networks towards global networks. Furthermore, traffickers are adaptive exploiting the possibilities offered by factors such as political instability in the Sahel and the expansion of national transport infrastructure in countries such as the United Arab Emirates.

Aas’s (2007) text *Globalization & Crime* explores the intersection of crime and globalization within the context of rising inequality, social interconnectedness and changing institutions. Relying on the influential work of scholars such as Castells (2000) Aas (2007) argues that global illicit flows are the mirror image of licit flows. That is, factors that encourage the movement of people, goods, capital and information across national borders in the licit sector have a similar impact in the illicit sector. For example, the erosion of state sovereignty has simultaneously favoured both money laundering in the illicit narcotics sector and tax avoidance in the licit financial sector. The author notes that this perspective is not without its critics, who say the historical and regional context should have more prominence.

Kelly, Maghan and Serio (2005) argue in their book *Illicit Trafficking* that the rise in trafficking generally, and the narcotics traffic specifically, is an unintended consequence of promoting economic globalization as an international development strategy. In other words, the authors set the global increase in flows of narcotics in a post-Cold War setting that has encouraged the liberalization of markets, societies, and technologies. Thus, factors influencing licit trade are also seen as influencing illicit trade. For example, innovations in information communication technology is seen as a possible factor in the proliferation of transnational narcotics trafficking. In addition, narcotics are seen as part of, and directly benefiting from, the increased flows of goods between nation states.

Singer (2008) in her book *Drugs and Development* looks at the impact that narcotics have played in the development of low and middle income countries from a critical perspective. She takes a historical look at both the first and second waves of globalization to find the factors that contributed to the rise of the licit and illicit drug trade. The first wave of globalization is the global increase in the flows of capital, labour, goods and information prior to World War I and the second wave of globalization describes a similar phenomenon observed after World War II. The author argues that the trade in narcotics has its roots in colonialism and capitalism. An example mentioned in her book is the link between the mercantilist policy of the British Empire and the proliferation of heroin in British India during the first globalization. Another example is the connection between the neoliberal policy of the United States and the spread of cocaine in the Andes during the second wave of globalization.

In Allen's (2005) text *An Industrial Geography of Cocaine*, the accelerated movement of labour, capital, commodities and information across national borders associated with globalization is seen as a catalyst for illicit flows generally and the traffic of narcotics specifically. Furthermore, the author argues that the fractured global regulatory framework has fostered the proliferation of transnational criminal networks such as narcotics traffickers. In addition, he argues that drug-trafficking-organizations are now participants in a global value chain and moving towards a more flexible decentralized model of production.

2.2 Theoretical Framework: The Gravity Model

For the purpose of my research, I have chosen the gravity model of international trade as it accurately predicts trade flows between countries and has been very successful empirically (Krugman, Obstfeld & Melitz, 2015; Anderson 2011; Anderson, 1979). In 1962, the economist Jan Tinbergen adopted Isaac Newton's law of universal gravitation to try to explain international trade flows (Tinbergen, 1962). This model, known as the gravity model, relates the bilateral trade flows between two countries to the size of their economy and the distance between them (Kalirajan, 2008). The Gravity Model of international trade is usually of the form:

Equation 1). $V_{ij} = A \times (Si \times S_j)/D_{ij}$

Where: V_{ij} is the trade volume between country i and country j; S_i is the size of country i's economy; S_j is the size of country j's economy; D_{ij} is the distance between country i and j; and the constant A acts as an aggregate of all independent variables that influence V_{ij} (Feenstra & Taylor, 2014).

The common interpretation of the gravity model is that a larger economy imports more goods because it has a higher income, and exports more goods, since it produces a greater variety of goods

(Krugman et al., 2015). Furthermore, we can interpret distance as accounting for transportation and other related costs (Bowen, Hollander & Viaene, 2012). Empirical tests of the gravity model tend to use gross domestic product (GDP) for economic size and the great circle equation for distance (Head, 2003). It is also common to augment the gravity model with relevant variables to avoid omitted variable bias and improve the fit of the regression (Head, 2003). Research into the gravity model has systematically found a positive relationship between economic size and the volume of international trade (Krugman et al. 2015). It has also found a negative relationship between distance and the volume of international trade.

The gravity model is an attractive choice to represent the transnational narcotics traffic because the assumptions of the model are compatible with the characteristics of the narcotics traffic, namely, imperfect competition and product differentiation. Anderson and Van-Wincoop (2003) arrived at the gravity model of international trade under the assumption of imperfect competition and product differentiation. A characteristic of the transnational narcotics traffic is that it operates under imperfect competition as trafficking networks have price-setting power. For instance, Skott and Jepsen's (2002) conclude that "a large body of empirical evidence shows that the market for hard drugs is imperfectly competitive" (p. 337). Another, characteristics of the narcotics traffic is that it demonstrates product differentiation, such as the difference between cocaine salt and crack cocaine. For example, Thornton (1998) highlights that product differentiation is evident in the varying incomes and tastes of illicit drug consumers. Therefore, as these two assumptions appear reasonable in the case of the narcotics traffic, this study favoured the Anderson and Van-Wincoop (2003) theoretical justification of the gravity model.

To explain the volume of narcotics traffic, this study modified the general gravity model and specified the econometric model as:

$$\text{Equation 2). } \hat{X}_{ij} = ke^{D'_{ij}\beta}$$

Where: $\hat{X}_{ij} = E[X_{ij}]$, X_{ij} is the dependent variable, k is a constant, e is the exponential function, D'_{ij} is a vector of independent variables, β is a vector of regression coefficients, i denotes the i^{th} country, and j denotes the j^{th} country (Bowen, Hollander & Viaene, 2012). The notable difference between the original model (Equation 1) and the specified model (Equation 2) is that the dependent variable has been replaced with the volume of the narcotics traffic between countries. If the specified model holds true, then a change in the size of trading partners' economies would affect the volume of narcotics traffic, and a change in the distance between trading partners would also affect the volume of narcotics traffic. Economists usually use the gravity model as a framework for total trade. However, authors have used it successfully for industry specific studies as well (Kahane, 2013; Leamer & Levinsohn, 1995)

There are generally two critiques directed towards the theoretical foundation of gravity models. The first is that the empirical model is detached from the broader trade theory discourse, and the second is that competing trade theories have appropriated the empirical model, reducing its usefulness. Anderson and Van-Wincoop (2003) are adamant that "contrary to what is often stated, the empirical gravity equations do not have a theoretical foundation" (p. 170). Yet, Anderson and Van-Wincoop (2003) provide in detail a theoretical foundation for the gravity model. For his part, Deardorff (1998) warns that as several competing theories of international trade reduce to the gravity model. For example, Eaton and Kortum (2002) generalized a version of the Ricardian model to account for the empirical findings of the gravity model, and Deardorff (1998) derived the gravity model from specific cases of the Heckscher Ohlin Samuelson (HOS) model.

2.3 Theoretical Framework: A Brief Overview of Competing Models

The gravity model is neither the only theory of international trade nor necessarily the best choice for the transnational narcotics traffic. Contending models include the Ricardian model, the Heckscher Ohlin Samuelson (HOS) model, the specific-factors model and the new economic geography. Each of these models has strengths and weaknesses in their application to the narcotics traffic. For example, a strength of the Ricardian model is that it can account for variations in techniques of production, yet it also relies on unrealistic assumptions (Feenstra & Taylor, 2014). Alternatively, HOS model could account for the impact of natural resources, such as agricultural land, in the production of narcotics; however, the model's explanatory power has been weak in pervious empirical studies (Bowen, Hollander & Viaene, 2012; Trefler, 1995; Bowen, Leamer & Sveikauskas, 1987). On the other hand, the specific-factors model could shed light on the role of policy in the narcotics traffic, yet this model does not focus on trade barriers (Feenstra & Taylor, 2014). Another option is the new economic geography that can model the clustering of firms in both space and time, although social scientists have yet to fully establish the mechanisms at play (Feldman, 2000). The following paragraphs will briefly introduce these models and some of their strengths and shortcomings.

Ricardian Model: The renowned classical economist David Ricardo outlined the Ricardian model in his book *On the Principles of Political Economy and Taxation* (1817). The Ricardian model, also known as the Ricardo-Torrens model, uses the concept of comparative advantage to explain the volume and patterns of trade, and supports the idea that trade is mutually beneficial (Ricardo, 1817; Feenstra & Taylor, 2014; Gandolfo, 2013). A country has a comparative advantage in the production of a good if it has the lowest comparative cost of production defined as "the ratio between the (absolute) unit costs of the same commodity in two countries" (Gandolfo, 2013, p. 12). The existence of varying comparative costs implies differences in techniques of production and thus the Ricardian model sees technology as the main economic factor explaining international trade. Technology and techniques of production certainly play a role in the narcotics traffic. For instance, technology, or the lack thereof, plays a role in the decision of Afghan farmers to grow opium poppies (Felbab-Brown, 2006). A serious critique of the Ricardian model is that its main function is normative, that is that the model is a simplification used to justify the social desirability of trade (Gandolfo, 2013). However, Gandolfo (2013) points out that the Ricardian model does have a positive function when conceptualized within complementary classical and neoclassical concepts. Empirically, the main success of the Ricardian model is establishing the existence of gains from trade (Leamer & Levinsohn, 1995). However, "the Ricardian one-factor model is a very poor setting in which to study the impacts of technologies on trade flows, because the one-factor model is just too simple" (Leamer & Levinsohn, 1995, p. 5). Furthermore, the Ricardian model makes a number of assumptions that are unlikely to hold for the illicit economy such as perfect competition, given that there are many barriers to entry in the illicit drug market.

HOS Model: Economists Eli Heckscher (1919), Bertil Ohlin (1933), Paul Samuelson and Wolfgang Stolper (1941) each contributed over several years to the Heckscher Ohlin Samuelson (HOS) model of international trade, also known as the factor abundance theory. The HOS model sees trade as a function of the relative abundance of factors-of-production between countries (Bowen et al., 2012). In other words, according to the HOS, we would expect that a country's endowment in resources would affect which goods are imported and which goods are exported (Feenstra & Taylor, 2014). The factor abundance theory is best when looking at questions of comparative advantage, profits, rents, interests, wages, and income distribution (Bowen et al., 2012). Early empirical studies based on the HOS model came across surprising results. One such example is the "Leontief paradox" where, at odds with the HOS model hypothesis, the United States exported goods intensive in its relatively scarce factor-of-production and imported goods intensive in its relatively abundant factor-of-production (Leontief, 1954). Later studies argued that this paradox may have been the result of a theoretically inappropriate definition of the relative abundance of factors-of-production and that the data did indeed support the HOS model (Learner, 1980). However, more recent empirical studies generally found that the HOS model either performs poorly or leads to counterintuitive conclusions leading authors to prefer alternate models that account better for factors such as technology (Trefler, 1995; Bowen et al., 1987).

Specific-Factors Model: To predict the winners and losers of international trade, economists often use the specific-factors model also known as the Ricardo-Viner model (Feenstra & Taylor, 2014; Feenstra, 2003). In broad strokes this theory states that, although trade helps the economy as whole, the factors of production specific to the import sector will lose from trade and the factors of production specific to the export sector will benefit. This is because, unlike HOS model, the specific-factors model considers what happens if some factors of production are immobile in the short and medium run (Bowen et al., 2012; Feenstra, 2003). There is empirical evidence that, in fact, returns to capital and the human capital of labour is industry-specific. Studies that rely on the specific-factors model have traditionally been cross-sectional analyses, yet this model is promising when it comes to dynamic pooled time-series analyses (Leamer & Levinsohn, 1995). Although the specific-factors model offers convincing explanations to topics such as trade protection, it is less relevant when it comes to predicting trade flows (Bowen et al., 2012; Feenstra & Taylor, 2014). Therefore, the specific-factors model is unlikely to provide a convincing answer to this study's research question.

New Economic Geography: Krugman in his paper *Increasing Returns and Economic Geography* (1991) sets out the basic model of the so-called new economic geography. This model aims to provide a general hypothesis for the centrifugal and centripetal forces that lead to the core/periphery dynamic observed in the concentration of firms (Fujita & Krugman, 2004). Specifically, in its most basic form the new economic geography model argues that the distribution of firms in a given region will depend on economies of scale and transportation costs. That is that, if the efficiency benefits of the firms forward and backwards linkages outweigh the costs associated with transportation an industrial core and an agricultural periphery will emerge. In the context of the international narcotics trade, high transportation cost has a centrifugal effect on the location of production whereas economies of scale centripetal effect on the location of firms. Thus this new economic geography could provide an explanation for why illicit drug production is dispersed over rural areas and concentrated in certain countries. Empirical studies of the new economic geography have found that when it comes to innovation and technology ally bound positive externalities do in fact exist (Feldman, 2000). Furthermore, these studies have found that language, culture and institutions are important factors when it comes to these externalities. However, the mechanisms at play in the new economic geography are not explicit and most studies have focused on the United States.

Chapter 3: Methodology

3.1 Data: Cross-Sectional and Pooled Time Series

Similar to most research into the underground economy, obtaining reliable data to reject or corroborate the hypothesis poses a unique challenge. As Elijah and Uffort (2007) state "estimating the size of various underground economies remains an inexact science at best" (p. 5). However, as Schneider (2005) points out in his article, the social sciences have made progress in estimating the size of the underground economy and its impact. This study has addressed the major issues associated with the statistical analysis of the data such as data accuracy, heteroscedasticity and endogeneity. Moreover, this study checked for the validity of the results by specifying several alternative models and conducting the corresponding post-estimation analysis.

An attractive feature of econometrics as an analytical tool is its affordability (Depelteau, 2011). This study relied on freely available data courtesy of organizations such as the UNODC (2016a), the World Bank (2016) and the CEPII (2016). Furthermore, several powerful statistical analysis software packages, such as R and Gretel are available as freeware, although this study used STATA 14 as it is a powerful and dependable software. Given the highly technical nature of econometrics and statistical research, the researcher's proficiency in mathematics and statistical theory was an asset. However, the major improvements in computing power of the last century have made statistical analysis more accessible and there were no technical barriers to estimating and testing the models.

Like many other studies that employ statistical analysis, the research relied on secondary data. However, direct, reliable and relevant secondary data is hard to find due to the secretive and illicit nature of the narcotics traffic. Some variables, such as the volume of the transnational narcotics traffic, are even arguably unobservable. Nevertheless, the research used several proxy variables to estimate the model (Equation 2) and test this study's hypothesis. The research used proxies that are likely highly correlated with the corresponding gravity model variables. If we accept the premise that the volume of the transnational narcotics traffic is unobservable, then legitimate proxies are the only option to empirically estimate and test the hypotheses outlined in this study. As long as these proxies correlate with the phenomenon of interest their use does not pose an immediate issue. That said, the results may change with the choice of proxies and it is important that the proxies be consistent with theory.

The target population of this study was a cross section of the world's countries from 2010 to 2014. The choice of years reflects the most recent five-year period for which data is available. Given that larger samples are, all other things being equal, more representative and lead to more generalizable conclusions, the research included every country for which data was available. Initially this study decided to limit the analysis to a year-by-year cross-section because panel data and time series data were ill-suited to the sample. That is, the data for the dependent variable consists of five convenience samples drawn from the population in five separate years. In other words, the pairs of countries observed are not the same year to year. This means, for instance, that a panel for 2010 to 2014 only has 53 pairs of countries compared to the 165 pairs that are in the 2010 cross section (see Table below). It goes without saying that this is a considerable drop it sample size and would limit the validity of the study. In other words, the data available for this project effectively precluded a true panel and time series analysis.

Table 1). Observations (n) in possible panel data configurations (years)

Panel (years)	**2010**	**2010 to 2011**	**2010 to 2012**	**2010 to 2013**	**2010 to 2014**
Observations (n)	165	81	65	58	53

As it is reasonable to assume that the volume of the transnational narcotics traffic varies over both space and time, this study will also incorporate a pooled time-series data design to supplement the study's cross section data design. By definition, a pooled time series is a data matrix where the variables that compose a series of different cross-sections are observed over a given period (Sayrs, 1989). Specifically, a Poisson pseudo maximum likelihood (PPML) dummy variable model adapted from the ordinary least squares dummy variable (LSDV) model will be estimated. The LSDV model introduces either time or space dummy variables to remedy for the bias in the ordinary least squares (OLS) model estimation of pooled data, but are otherwise identical (Stimson, 1985). Other studies, such as Li (2004), looking at the transnational economic globalization between countries have employed similar pooled time-series designs.

The principal strength of pooled cross section analysis is that it allows variations in both units of time and space to be analyzed (Stimson, 1985). In addition, pooled cross sections may be the only data design available to social scientists faced with cross section data with few observations or time-series data with few points in time (Sayrs, 1989). Concretely, the main advantage of pooled time-series data to this study is that it allows the inclusion of certain dynamic processes into our analysis. Contrary to its pooled OLS model counterpart, the inclusion of dummy variables in LSDV model does mitigate for factors such as bias, heteroscedasticity, autocorrelations and stationarity.

Although, Stimson (1985) sees great potential in pooled time-series data designs he is also cautious of their many drawbacks. In this case, the LSDV model "should be used with some caution as it could be less efficient than other estimators and information could be lost when the X vector contains time invariant variables". (Sayrs, 1989, p. 4). Furthermore, Sayrs (1989) warns that researchers need to keep in mind the meaning of the aggregations in pooled time-series data when interpreting the results. Moreover, the omission of a dummy variable to avoid the dummy variable trap effectively creates an arbitrary reference point for the estimation (Stimson, 1985). Even, with these drawbacks, Stimson's (1985) argues that "where unit effects are present and concern for estimator efficiency is not paramount LSDV is a reasonable choice" (p. 945).

3.2 Dependent variable: Narcotics Seizures

The research used data made available by the UNODC (2016a) to estimate the volume of narcotics traffic between countries. Specifically, the research employed a method inspired by the 2010 World Drug Report (United Nations, 2010) to estimate a proxy for the volume of narcotics traffic. As part of its activities, the UNODC "collects analyses and reports data on drug trafficking trends including arrests, seizures, price and purity of illicit drugs submitted by the Member States through the Annual Reports Questionnaires (ARQ)" (UNODC, 2016b). Member states revised and adopted the ARQ in 2010. The aim of the ARQ is to "enable the monitoring of and the biennial reporting to the Commission on the implementation by Member States of the Political Declaration and Plan of Action on International Co-operation towards an Integrated and Balanced Strategy to Counter the World Drug Problem" (ARQ, 2016).

The UNODC collects disaggregated data on significant individual drug seizures (IDS) by member states from 2010 to 2014 (UNODC, 2016a). The information, where available, includes the country, seizure date, drug name, amount, drug unit, producing country, country obtained/departure country, destination country. The main strength of this data source is that for entries that specify a producing country, a country obtained/departure country, and a destination country it is possible to construct a proxy of the transnational narcotics traffic. The main limitation of this source is that it only documents significant individual drug seizures defined as: opium, cannabis herb, cannabis resin and cannabis plants ≥ 1000 grams; heroin, morphine, cocaine ≥ 100 grams; psychotropic substances ≥ 100 grams, all quantities of seizures trafficked by mail and all quantities of new psychoactive substances. In other words, seizures in small quantities, such as those for personal consumption, are not recorded in the data. Even with these limitations, this study chose the IDS data to construct a proxy (*tradevolume*) for the transnational narcotics traffic, given the difficulties in finding reliable macro data on illicit activities.

The top 10 most seized narcotics, reported in the UNODC's (2016a) IDS dataset, are listed below in Table 2. *Drug Name* refers to the illicit psychoactive substance; *Percent* is the percentage of the total seizure number; and *Cum.* is the cumulative percentage. In Table 2 we can see that, for the five-year period, tetrahydrocannabinol (THC), cocaine salt and heroin are first, second and third respectively in terms of seizure numbers. Furthermore, Table 2 illustrates that the top 10 most seized narcotics makeup between 97.54, 2014, and 99.62, 2010, of the total seizure numbers reported in the UNODC's (2016a) IDS dataset.

Table 2). Top 10 Most Sized Narcotics 2010 to 2014

2010			2011			2012		
Drug Name	Percent	Cum.	Drug Name	Percent	Cum.	Drug Name	Percent	Cum.
THC	47.26	47.26	THC	45.35	45.35	THC	49.96	49.96
Cocaine Salt	31.41	78.67	Cocaine Salt	25.35	70.70	Cocaine Salt	26.21	76.17
Heroin	13.41	92.08	Heroin	11.06	81.76	Heroin	13.30	89.48
Mephedrone	4.05	96.13	Ephedrine	4.98	86.74	Ephedrine	2.40	91.88
Cathinone	1.18	97.31	Methcathione	4.29	91.04	Amphetamine	2.03	93.91
Amphetamine	0.61	97.92	Cathinone	3.06	94.09	Methcathinone	1.63	95.54
Methamphetamine	0.57	98.49	Amphetamine	2.38	96.47	Methamphetamine	1.06	96.61
Methcathione	0.44	98.93	Methamphetamine	1.19	97.67	Cocaine Crack	0.89	97.50

Ephedrine	0.29	99.22	2C-B	0.38	98.04	MDMA	0.40	97.90
MDMA	0.21	99.43	Diazepam	0.28	98.32	Methadone	0.35	98.25
2013			**2014**					
Drug Name	Percent	Cum.	Drug Name	Percent	Cum.			
THC	52.75	52.75	THC	42.49	42.49			
Cocaine Salt	23.68	76.43	Cocaine Salt	30.23	72.71			
Heroin	11.41	87.84	Heroin	14.81	87.52			
Cocaine Crack	2.06	89.90	Ephedrine	3.33	90.86			
Amphetamine	1.96	91.86	Amphetamine	2.43	93.28			
Ephedrine	1.67	93.54	2C-B	1.50	94.78			
2C-B	0.97	94.51	MDMA	0.96	95.73			
Methamphetamine	0.96	95.47	Methamphetamine	0.76	96.49			
MDMA	0.76	96.22	Methadone	0.59	97.08			
Methcathinone	0.74	96.97	Methcathinone	0.56	97.65			

Even though we expected the dependent variable to take on zero values in some cases, for example seizures between Bahrain and Lithuania, the nature of the IDS dataset (UNODC, 2016) precluded this result. In other words, the IDS dataset (UNODC, 2016) by definition only records self-reported significant non-zero seizures by member states. In practice, the absence of seizures between Bahrain and Lithuania resulted in no observation being recorded in the sample. Therefore, all statistics, estimates and conclusions drawn from the IDS dataset (UNODC, 2016) are for countries where at least one seizure was reported to the UNODC. The absence of reported seizure between two countries may indicate either that no seizures occurred or that seizures occurred but went unreported. Hence, the study was careful not to draw any conclusions unwarranted by the data.

This study used a novel “dosage” approach to unit standardization to overcome the challenge posed by the many measures and forms of narcotics found in the UNODC’s (2016a) IDS dataset. The different units prevented the research from summing drug seizures by country and year, and the different drug types curtailed meaningful comparisons between countries. For example, without a unit standardization approach this study could not sum seizures in kilograms with seizures in tablets, and compare seizures of heroin with the seizure of cocaine.

In the toxicology and pharmacology literature on drugs, the term dose effect denotes the clinical data on the generally observed effects of various doses of psychoactive substances in humans (Barceloux, 2012, p. XIII). This study used this wealth of data to establish estimates of minimal doses required for an average individual to experience an objective difference between a narcotic and a placebo. These are useful estimates because, if we know the type of drug and the quantity in weight, it is possible to systematically transform the unit in which seizures were reported into doses. For example, knowing that "the typical single dose of heroin in a drug-dependent individual is approximately 150–200 mg" (Barceloux, 2012, p. 552), and that South Africa seized 20 kilograms of heroin travelling from Pakistan (UNODC, 2016a), we can estimate that this seizure represents between 100,000 and 133,333 doses.

From 2010 to 2014, the top 10 most sized narcotics reported in the UNODC's (2016) IDS dataset included 15 different illicit drugs. These narcotics are listed below, in Table 3, along with the working minimal dose and its source in the literature. Minimal doses very considerably, and the figures below reflect conservative estimates for an average individual.

Table 3). Minimal Dose for Top 15 Most Sized Illicit Drugs 2010 to 2014

Drug Name	Minimal Dose	Source
Amphetamine	50 mg	Barceloux (2012, p. 7)
Cathinone	31 mg	Barceloux (2012, p. 58)
Cocaine Crack	50 mg	Barceloux, 2012 (pp. 810–811)
Cocaine Salt	25 mg	Barceloux (2012, p. 812)
Diazepam	20 mg	Griffiths et al. (1984, p. 150)
Ephedrine	1,450 mg	Barceloux (2012, p. 236)
Heroin	150 mg	Barceloux (2012, p. 552)
LSD	100 µg	Barceloux (2012, p. 455)
MDMA	100 mg	Barceloux (2012, p. 129)

Mephedrone	125 mg	Winstock et al. (2011, p. 1993)
Methadone	10 mg	Barceloux (2012, p. 582)
Methamphetamine	30 mg	Barceloux (2012, p. 24)
Methcathione	80 mg	Barceloux (2012, p. 121)
THC	16 mg	Barceloux (2012, p. 892)
2C-B	8 mg	Barceloux (2012, p. 175)

A possible concern with the “dosage” approach to unit standardization is that it assumes that the parameters are consistent across narcotics that require agricultural inputs, like THC, heroin, and cocaine salt, and those that do not such as MDMA, amphetamine and LSD. However, drugs requiring agricultural inputs dominate by far the sample. For instance, in Table 2 we observe that from 2010 to 2014 the top three most seized narcotics, THC, cocaine salt and heroin represented between 81.76% and 92.08% of all seizures depending on the year. This study therefore hypothesizes that separating the “agricultural” and “non-agricultural” narcotics will simply lead to similar results for “agricultural” narcotics and an insufficient sample size for “non-agricultural” narcotics.

Another possible concern with the “dosage” approach to unit standardization is how it compares to a more traditional “street value” approach. The answerer is that there are serious conceptual and practical limitations to a “street value” approach. Conceptually, factors such as imperfect information, price discrimination and other market failures lead to highly variable retail prices, that would require unrealistic assumptions. For instance, most transactions of narcotics are conducted in round prices for the sake of expediency and the quality or the product is often what will vary with market fluctuations (Caulkins & Reuter, 2006). In addition, huge difference in price and quality are found over time and place, even within the United States (Reuter and Greenfield, 2001). Practical limitations also emerge in the availability and reliability of market value prices for narcotics. For example, the UNODC (2016c) does have a dataset of retail prices for six key narcotics but the most recent data for some countries is as old as 2004 and there are only typical retail prices for approximately 80 countries depending on the substance. Moreover, "buyers cannot report a price in dollars per standardized unit, but only how much they spent on some quantity of white powder, the contents of which is unknown" (Reuter and Greenfield, 2001, p. 169).

3.3 Independent Variables: Distance, Economic Size and Controls

Table 4 list all of the study's independent and control variables along with their name, code, source, expected sign and possible bias. These variables are then explored in greater detail in the following section.

Table 4). List of Independent and Control Variables

Name	**Code**	**Source**	**Hypothesis**	**Direction of Possible Bias**
Weighted Distance	*distwces*	CEPII (2016)	expected sign < 0	Left
Source Country GNI	*sou_gni*	World Bank (2016)	expected sign < 0	Left
Destination Country GNI	*des_gni*	World Bank (2016)	expected sign > 0	Left
Common Languages	*comlang_ethno*	CEPII (2016)	expected sign > 0	Left
Colonial Ties	*colony*	CEPII (2016)	expected sign > 0	Left
Source Country Cereal Yields	*sou_cy*	World Bank (2016)	expected sign < 0	Left
Destination Country Cereal Yields	*des_cy*	World Bank (2016)	expected sign < 0	Left
Source Country Total Police Personnel	*sou_tpr*	UNODC (2016d)	expected sign ≠ 0	Unspecified
Destination Country Total Police Personnel	*des_tpr*	UNODC (2016d)	expected sign ≠ 0	Unspecified

Distance: Descriptive and empirical work on the impacts of distance on international trade have found persistent effects time and again (Leamer & Levinsohn, 1995). In other words, "distance matters, and it matters a lot" (Leamer & Levinsohn, 1995, p. 45). Leamer & Levinsohn (1995) attribute this relationship primarily to proximity acting as a comparative advantage in trade. Traditionally, the standard measure of distance between countries has been distance measured by the great circle equation (Feenstra & Taylor, 2014). In a similar fashion, this study used the CEPII's measure of the distance between the largest metropolitan areas of countries, measured by population, weighted for the internal population distribution (*distwces*) (Mayer & Zignago, 2011). The CEPII publishes data on various distances of economic importance, such as *distwces*, in its GeoDist dataset (CEPII, 2016).

This study used the *distwces* equation to calculate distances between country i and j as follows:

Equation 3). $d_{ij} = \left(\sum_{k\in i}(pop_k/pop_i)\sum_{l\in j}(pop_l/pop_j)d_{kl}^{\theta}\right)^{1/\theta}$

where pop_k is the population of agglomeration k in country i and pop_l is the population of agglomeration l in country j (Mayer & Zignago, 2011). Furthermore, the parameter θ quantifies the responsiveness of trade flows to bilateral distance d_{kl}. It is worth noting that “the distwces calculation set’s θ equal to -1, which corresponds to the usual coefficient estimated from gravity models of bilateral trade flows” (Mayer & Zignago, 2011, p. 11). This equation for calculating distances is more consistent and has less potential for bias than the great circle equation because it gives appropriate weight to national and international distances (Head & Mayer, 2002). Furthermore, this study chose *distwces* as it is consistent with past estimates of the gravity model (Mayer & Zignago, 2011).

As the CEPII’s *distwces* looks only at one component of distance, it possibly underestimates the true distance. Thus we can expect that the variable is biased to the left. The expected sign for distance is negative as countries that are further apart are less likely to trade in narcotics. Morselli, Giguère, and Petit (2007) found that drug traffickers will maintain close links to achieve greater efficiency in their enterprise, and this would support the idea that distance is an important factor in the transnational trade of narcotics. Furthermore, Allen (2005) argues that there are many factors that contribute to competitive advantages between national and international drug producing organizations, but that geography and market access certainly plays a role.

Economic Size: The standard measure for economic size has traditionally been GDP (Feenstra & Taylor, 2014). However, this study used the gross national income (GNI) of the observed countries, as it accounts better for inflows and outflows of income (OECD Observer, 2005). In other words, the advantage of using GNI is that it is appropriate for international comparisons, and readily available. This study used the World Bank's (2016) data on GNI, calculated in purchasing power parity (PPP) in current international dollars based on the 2011 ICP round. Therefore, this study's measures of economic size are source country GNI (*sou_gni*) and destination country GNI (*des_gni*). A possible source of bias is that national income statistics, such as the World Bank's measure of GNI, do not include the shadow economy. The shadow economy is comprised of illicit activities and unreported, or underreported, licit activities. A study from 2013 found that the shadow economy could represent 18.4% of the European Union's official GDP statistics (Schneider, 2015). Thus we can expect the variable to be biased to the left.

The expected sign for *sou_gni* is negative. That is, we expect that the transnational trade of narcotics will be a decreasing function of the source country's economic size. The justification for this is that drug trafficking organizations locate their supply activities in low-income and middle-income countries and cater to the demand in high-income countries (Castells, 2000). On the other hand, the expected sign for *des_gni* is positive. That is, we expect that the transnational trade of narcotics will be an increasing function of the destination country's economic size. Empirical research has found this to be the case for the illicit trade of guns in the United States (Kahane, 2013). And this could also be true of the global narcotics traffic as greater economic size may translate into greater demand for narcotics. If this is in fact the case, it would be consistent with Chin's (2009) qualitative research.

Control Variables: Research has established that cultural affinity, often approximated by a common official language, likely has an impact on the volume of international trade (Krugman et al. 2015). The CEPII publishes data on languages spoken and colonial heritage that can be used to proxy cultural affinity. For example, the CEPII (2016) dataset GeoDist contains data on the languages spoken by over 20 percent of the population (*comlang_ethno*) and long-term colonizers (*colony*) for most countries. The strength of using the language *comlang_ethno* is that it addresses the critique that the official language may be a poor indicator of cultural affinity. Yet, *comlang_ethno* is a snapshot of the world in 2011, and the proportions of the population that speak certain languages have changed since then. Thus, the study also used the CEPII's measure of long-term colonization (*colony*) as an alternative proxy for this variable (CEPII, 2016).

As *comlang_ethno* and *colony* only account for certain facets of culture, they are likely to underestimate the cultural affinities between trade partners. Thus we can expect the variable to be biased to the left. The expected sign for cultural affinity is positive. That is, we expect that the transnational trade of narcotics will be an increasing function of *comlang_ethno* and *colony*. This is a reasonable hypothesis, given that cultural affinity would facilitate the traffic of narcotics through information, communication and social networks. In their landmark paper, Alchian and Demsetz (1972) highlight the central role that the communication of information plays in inter and intra firm competition. Furthermore, Mcillwain (1999) argues that human relationships and social networks form the basis of organized crime. Additionally, cultural affinity is a robust indicator of bilateral trade even when controlling for complimentary effects (Felbermayr & Toubal, 2010). However, this issue is not clear cut, with Kelly, Maghan and Serio (2005) arguing that trafficking networks are more than ever collaborating outside of traditional ethnic and racial confines.

This study used the World Bank's (2016) measure of cereal yield (*cy*) in kilograms per hectare as a proxy for the role of agricultural productivity. The three most common narcotics in terms of seizure number are all plant derived, THC from the marijuana plant, cocaine from the coca leaf and heroin from the opium poppy. Thus, agricultural productivity could be a relevant independent variable and greater cereal yields may pose an opportunity cost to growing narcotics. We expect countries with high cereal yields to be less likely to produce and export narcotics and conversely we expect countries with low cereal yields to be more likely to produce and export narcotics. The strength the World Bank's (2016) measure of agriculture productivity *cy* is that it is consistent, easily available, and a measure of comparative advantages in the production of narcotics.

As *cy* does not include data on "cereal crops harvested for hay or harvested green for food, feed, or silage and those used for grazing", this proxy likely underestimates overall yields (World Bank, 2016). Thus we can expect the variable to be biased to the left. The expected sign for agricultural productivity is negative. That is, we expect that the transnational trade of narcotics will be a decreasing function of both source and destination country cereal yields (*sou_cy* and *des_cy*). The logic behind this relationship is that individuals in areas of low agricultural productivity face a lower opportunity cost to producing narcotics. For example, Tullis (1987) mentions that the coca trade in Bolivia and Peru "is labour-intensive, decentralized, growth poles oriented, cottage industry promoting, and foreign exchange earnings" and thus attractive to marginalized farmers. A further example, would be from Afghanistan where, even with subsidized wheat and fruit prices, the substantial sunk cost associated with growing licit crops push many poor farmers to grow opium poppies (Felbab-Brown, 2006).

A countries' law enforcement efforts could be the source of a substantial omitted variable bias. This is because, quantities of narcotics seized may reflect law enforcement activities and not the true volume of narcotics trafficking. However, it would be possible to control for this bias by including a measure of law enforcement. One such measure is the police presence in the chosen countries. Thus, given the availability of data, this study's proxy for law enforcement for both source and destination countries (*sou_tpr* and *des_tpr*) is the UNODC's measure of total police personnel rate per 100,000 individuals at the national level (UNODC, 2016d).

Both *sou_tpr* and *des_tpr* are imperfect measures of law enforcement efforts and the direction of a possible bias is not immediately apparent. Additionally, the expected sign for law enforcement is uncertain, because increasing law enforcement efforts will both deter the illicit trade of drugs and increase the likelihood of seizures. (*sou_tpr* and *des_tpr*). The importance of including a measure of law enforcement is illustrated in Kahane's (2013) econometric study, *Understanding the Interstate Export of Crime Guns*, where such a measure was statistically significant. Kahane (2013) also highlighted that law enforcement activities can both increase the number of seizures and act as a deterrent to trafficking.

3.4 Estimation Approach: PPML

The parametric alternative that has emerged from the quasi-or-pseudo maximum likelihood literature to the log-linearized OLS estimation of the gravity model will be referred to as the PPML estimator. This estimator is a generalized linear model (GLM) with a logarithmic link function and a Poisson distribution. Link functions allow parameters to be estimated for non-linear model without changing the multiplicative nature of the theoretical model. The study chose the PPML estimator over the log-linear OLS estimator because the PPML provides parameters in the original scale, does not require the definition of ln (0), and allows the assumption of homoscedasticity to be relaxed. In other words, the PPML estimation of the gravity model is consistent (Gourieroux, Monfort & Trognon, 1984), allows heteroscedasticity (Silva & Tenreyro, 2006), and avoids back transformation bias (Cox et al., 2008). Furthermore, the PPML command in STATA also addresses issues related to the Poisson command by checking for the existence of the estimates (Silva & Tenreyro, 2011). Therefore, it was the parametric estimate of choice for this study.

As linear models are not appropriate for small samples of positive values, non-linear models are an attractive alternative (Gourieroux et al., 1984). Traditionally, limited to count-dependent variables, Poisson estimation is growing in popularity for non-linear continuous variables (Silva & Tenreyro, 2010). Although, the Poisson estimator remains the model of choice for count data, it has also been shown to be consistent, unbiased and efficient for continuous positive variables (Silva & Tenreyro, 2006).

The Poisson model's standard assumptions are that the i^{th} observation of y follows both a Poisson and independent distribution (Gourieroux et al., 1984). However, by including a specification error in the Poisson model, the conditional variance is allowed to vary from the conditional expectation. Furthermore, Poisson models with a specification error are consistent, and asymptotically normal, even if their probability density function is unknown. That is, Poisson models do not require the assumption of independence between past and present to hold. In practice this means that by using an Eicker—Huber—White robust estimator of variance we can relax the classical Poisson assumptions that E (yj) = Var (yj) and Var (yj) is constant for all j (Gould, 2011). This means that the PPML estimator that will be consistent as long as E (yi | xi) = exp (xi'β) (Silva & Tenreyro, 2010).

There is a compelling case to favour PPML estimation over log-linear OLS estimation. For example, Monte Carlo simulations and a gravity model case study corroborates that the PPML model is the preferred alternative, as it is consistent under heteroscedasticity (Silva & Tenreyro, 2006). Unlike a logarithmic transformation function such as log-linear OLS, a logarithmic link function such as PPML generates results in the original measure and scale (Cox, Warburton, Armstrong & Holliday, 2008). This is a desirable property because it avoids back transformation bias. However, Silva and Tenreyro (2010) demonstrated that, under certain data configurations, the PPML estimates are undefined, and could generate a spurious convergence of the maximization algorithm. For example, the PPML estimates may not exist when there is an important proportion of zero observations in the sample. Therefore, Silva and Tenreyro (2010) propose a method of identifying, and dropping, the independent variables responsible for the non-existence of the PPML estimates. This was the preferred PPML estimation method for this study.

It is worth mentioning here that endogeneity remains an issue for estimations of the gravity model. For instance, it is no secret that geography matters for development (Sachs, 2003), therefore we would expect a relationship between *distwces*, *sou_gni* and *des_gni*. This implies a certain level of endogeneity in the gravity model generally as distance influences both the volume of trade, and the economic size of countries. However, authors have found economic size strongly correlated to the volume of international trade even when controlling for endogeneity with the use of instrumental variables (Cyrus, 2002). Grange, Troncoso, Ibeas and González (2009) were also able to control for endogeneity in the gravity model with the use of proxies, yet they conclude that the endogeneity in the OLS estimation of the gravity model did not introduce a notable bias. As this study relies primarily on proxy variables, endogeneity bias does not appear to pose a major concern.

Chapter 4: Results

4.1 Summary Statistics: Dependent, Independent and Control Variables

Narcotics Seizures (*tradevolume*): *Tradevolume* has sample sizes ranging from 163 in 2010 to 331 in 2012 with a total of 1,186 for the 2010 to 2014 period. Although the means, listed in Table 3 below, for *tradevolume* are large, ranging from 5,064,537 in 2012 to 1.09e+07 in 2010, they appear reasonable considering that observations are the sum narcotics seized between two countries denoted in doses. In other words, the sample sizes are sufficiently large and the means are high but within the realm of possibilities. The minimum value of *tradevolume* for all five years was 1.22 in 2010 and corresponds with traffic from the Netherlands to the Russian Federation. The maximum value of *tradevolume* for all five years was 1.28e+09 in 2011 and corresponds with traffic from Morocco to Spain. The transportation method may explain this great difference between the minimum and maximum. For example, commercial sea was the transportation method for 35% of seized traffic between Morocco and Spain, whereas commercial post was the transportation method for all three seizures between the Netherlands and the Russian Federation. This study found four problematic outliers that were dropped from the sample. For instance, on the lower end, in 2012 there was only a single seizure of 0.0071722 doses (0.143 g. of acetylated opium) from Ukraine to the Russian Federation. On the higher end, in 2013 an unlikely high seizure of cannabis (2,295,216 kg) was reported between Guatemala and Mexico. *Tradevolume*'s distribution for each individual year, as well as the entire period, is severely left-skewed and positive non-zero. On the other hand, the distribution of the natural logarithm, of *tradevolume* for each individual year, as well as all the entire period, is approximately normal indicating that *tradevolume* is likely log normally distributed (graphs 1 to 6 in annex).

Table 5). Summary Statistics Narcotics Seizures (*tradevolume*)

Proxy of Trade Volume					Proxy of Trade Volume for 2010					Proxy of Trade Volume for 2011				
	Percentiles	Smallest				Percentiles	Smallest				Percentiles	Smallest		
1%	6.5	1.22			1%	4	1.22			1%	8.078	1.45		
5%	104.9831	1.45			5%	3374.624	4			5%	1187.5	8.078		
10%	3374.624	1.8	Obs	1,186	10%	10493	56.65	Obs	163	10%	5000	16.8	Obs	193
25%	26800	2.06	Sum of Wgt.	1,186	25%	45400	212.08	Sum of Wgt.	163	25%	25548	31.6666	Sum of Wgt.	193
50%	114895.4		Mean	7508369	50%	170698		Mean	1.09e+07	50%	106704		Mean	1.07e+07
		Largest	Std. Dev.	5.28e+07			Largest	Std. Dev.	6.96e+07			Largest	Std. Dev.	9.33e+07
75%	976154.5	4.49e+08			75%	983120	1.18e+08			75%	1006236	5.70e+07		
90%	9121538	5.54e+08	Variance	2.79e+15	90%	9210680	1.24e+08	Variance	4.85e+15	90%	1.02e+07	5.87e+07	Variance	8.71e+15
95%	2.58e+07	8.38e+08	Skewness	16.90859	95%	2.34e+07	2.36e+08	Skewness	10.64913	95%	2.76e+07	1.97e+08	Skewness	13.17669
99%	1.40e+08	1.28e+09	Kurtosis	350.6663	99%	2.36e+08	8.38e+08	Kurtosis	124.4975	99%	1.97e+08	1.28e+09	Kurtosis	179.1667
Proxy of Trade Volume for 2012					**Proxy of Trade Volume for 2013**					**Proxy of Trade Volume for 2013**				
	Percentiles	Smallest				Percentiles	Smallest				Percentiles	Smallest		
1%	16	2.06			1%	6	2.16658			1%	4.8	1.8		
5%	158.5	15.5			5%	43.75	3.276			5%	15.2	4.44		
10%	6200	16	Obs	331	10%	651.659	6	Obs	275	10%	143.846	4.8	Obs	224
25%	31928	16	Sum of Wgt.	331	25%	24236	6.5	Sum of Wgt.	275	25%	15170.25	4.8	Sum of Wgt.	224
50%	110055		Mean	5064537	50%	130000		Mean	6231185	50%	96228.5		Mean	7466609
		Largest	Std. Dev.	2.81e+07			Largest	Std. Dev.	2.66e+07			Largest	Std. Dev.	4.18e+07
75%	927437.5	7.97e+07			75%	1190595	1.92e+08			75%	812600	1.06e+08		
90%	7134000	1.40e+08	Variance	7.92e+14	90%	8720035	1.98e+08	Variance	7.10e+14	90%	1.06e+07	1.31e+08	Variance	1.75e+15
95%	2.27e+07	1.40e+08	Skewness	12.71691	95%	2.63e+07	2.19e+08	Skewness	6.614479	95%	2.58e+07	2.13e+08	Skewness	10.78667
99%	7.97e+07	4.49e+08	Kurtosis	191.8228	99%	1.98e+08	2.19e+08	Kurtosis	49.2361	99%	1.31e+08	5.54e+08	Kurtosis	134.7812

Weighted Distance (*distwces*): We know the distance between pairs of countries (*distwces*) for all 193 United Nations member states. Therefore, the number of observations in our sample corresponds to our total number of observations for *tradevolume* or 1,186. The mean of *distwces* was 5538.797. The minimum value of *distwces* was 123.2928 between Guatemala and El Salvador. And the maximum was 19,067.9 between Paraguay and Hong Kong. This is consistent with our understanding of distances between countries. The distribution of *distwces* is bimodal, left-skewed and positive non-zero (Graph 7 in the annex). The complete summary statistics are displayed in Table 12 in the annex.

Source and Destination Country GNI (*sou_gni* and *des_gni*): The sample has the same number of observations for *sou_gni* and *des_gni.* For instance, *sou_gni* has observations ranging from 163 in 2010 to 331 in 2012 with a total of 1,186 for the 2010 to 2014 period. Correspondingly, *des_gni* also has observations ranging from 163 in 2010 to 331 in 2012 with a total of 1,186 for the 2010 to 2014 period. This study also observed that for 2010 to 2014 *sou_gni*'s overall mean was lower than that of *des_gni*'s, at 1.17e+12 and 1.51e+12 respectively. The smallest observation for *sou_gni* and *des_gni* was Saint Vincent and the Grenadines in 2010 at 1.043e+09. Whereas the largest observation for *sou_gni* and *des_gni* was the United States in 2014 at 1.789e+13. In both cases, it is unsurprising that the maximum is the largest economy in the world the minimum is a small island nation. *Sou_gni*'s yearly and total distributions are left-skewed and positive non-zero (see Graph 8 in annex). Likewise, *des_gni*'s yearly and total distributions are left-skewed and positive non-zero (see Graph 9 in annex). The detailed summary statistics are displayed in Tables 13 and 14 in the annex.

Common Language (*comlang_ethno*) and Colonial Link (*colony*): We know *comlang_ethno* and *colony* for most United Nations member states, and their number of sample observations again corresponds to our total number of observations for *tradevolume* or 1,186. *Comlang_ethno* has a mean of 0.1804384. This implies that 214 pairs of countries in our sample share a language spoken by 20% or more of the population. In contrast, *colony* has a mean of 0.1281619. This implies that 152 pairs of countries in the sample share a colonial link. As both *comlang_ethno* and *colony* are dummy variables the minimum is by definition equal to zero and the maximum equal to one. The complete summary statistics are listed in Table 15 in the annex.

Source and Destination Country Cereal Yield (*sou_cy* and *des*_cy): From 2010 to 2014, the number of observations in the sample for *sou_cy* and *des*_cy are 1,178 and 1,183 respectively. The number of observations is adequate for the research. The mean for *sou_cy* ranged from 3,952.826 in 2012 to 4,252.942 in 2014, with an overall mean of 4,074.099. Whereas, the means for *des_cy* were higher and ranged from 4,649.197 in 2012 to 4,968.835 in 2013, with an overall mean of 4,811.522. The smallest observation for *sou_cy* in the period was 177.8 and corresponds to Cabo Verde in 2011. And the largest observation for *sou_cy* in the period was 18,774.2 and corresponds Saint Vincent and the Grenadines in 2010. Oddly enough, Cabo Verde and Saint Vincent and the Grenadines are both small island nations. The smallest observation for *des_cy* in the period was 35.7 and corresponds to Cabo Verde in 2014. And the largest observation for *des_cy* in the period was 21,844.7 and corresponds to Kuwait in 2014. There is a large spread in both *sou_cy* and *des_cy*, which reflects the major differences in global cereal yields. The distributions of both *sou_cy* and *des_cy* are left-skewed and positive non-zero for 2010 to 2014 (graphs 10 and 11 in the annex). The complete summary statistics for *sou_cy* and *des_cy* are displayed in Tables 16 and 17 in the annex.

Source and Destination Country Total Police Personnel (*sou_tpr* and *des_tpr*): From 2010 to 2014, there are 948 and 1,053 observations in the sample for sou_tpr and des_tpr respectively. The number of observations for *sou_tpr* and *des_tpr* in the sample are small relative to the other control variables. In the study period, *sou_tpr*'s overall mean was 332.2807 and *des_tpr*'s overall mean was higher at 369.7085. The smallest observation in the period for *sou_tpr* was 17.3 and corresponds to

Cameroon in 2013, and the equivalent observation for *des_tpr* was 84.5 and corresponds to Hungary in 2013. The largest observation for both *sou_tpr* and *des_tpr* was 891.3 and corresponds to Grenada in 2010. The overall sample distribution of both *sou_tpr* and *des_tpr* is left-skewed and positive non-zero (graphs 12 to 13 in the annex). The complete summary statistics for *sou_tpr* and *des_tpr* are displayed in Tables 18 and 19 in the annex.

Missing observations are a reality for this study as the main dataset is an amalgamation of select data from the UNODC's (2016a) IDS, the World Bank's (2016) World Development Indicators and the CEPII's GeoDist (2016). It is worth noting that *sou_cy* is missing observations for Hong Kong and Baharain and the *des_cy* is missing observations for Iceland, Singapore and Hong Kong. Moreover, there are a large number of missing observations for both *sou_tpr* and *des_tpr*. For instance, *sou_tpr* is missing observations for approximately 20% of the source countries in the sample and *des_tpr* is missing observations for roughly 11% of the destination countries in the sample. This implies that the addition of *sou_tpr* and *des_tpr* as control variables comes at the cost of fewer observations. This could limit the validity of models that includes *sou_tpr* and *des_tpr*.

4.2 Analysis: Models and Estimations

This study proposed a core specification of the gravity model, as well as four additional augmented gravity models, for the transnational narcotics traffic. Tables 6 through 10 below compare the PPML estimation results of these five gravity models, for 2010 to 2014. The following paragraphs also touch on the possible covariance within the data. This is a useful exercise as it highlights possible autocorrelations of the variables. When reading Tables 6 through 10, the leftmost column contains the name of the variables and statistics, and the top row contains the year. Stars denote the z-test statistical significance. In addition, one star is equal to the significance at the 10% confidence level, two stars is equal to the significance at the 5% confidence level and three stars is equal to the significance at the 1%

confidence level. Furthermore, *n* is the number of observations and *r2* is the pseudo-R-squared coefficient of determination.

Table 6 below lists the PPML estimation results of model 1 for pooled data and individual years.

Equation 4). Model 1 = *tradevolume* = f(*distwces, sou_gni*, *des_gni*)

By definition, model 1 is the quintessential gravity model and its independent variables are composed of *distwces, sou_gni* and *des_gni*. Model 1 lays out a baseline for our estimations as it is the gravity model in its simplest form. That said it likely suffers from omitted variable bias due to the lack of control variables. Looking at the variables from top to bottom, first we see that *distwces* is consistent in sign yet not statistically significant in all data configurations. Second, we see that *sou_gni* is consistent in sign and statistically significant in all but one data configurations. Third we see that *des_gni* is consistent in sign and only statistically significant in two data configurations. Fourth, the four dummy variables for year (dummy2010, dummy2011 … dummy2013) in the pooled time-series data configuration are not statistically significant. And fifth the constant (_cons) is consistent in sign and statistically significant in all data configurations. Looking at the statistics, 2010 has only 163 observations whereas the pooled data has 1186. Globally, the results for *distwces* and *sou_gni* are promising and in line with our hypothesis. However, *des_gni* does not appear correlated to *tradevolume* in model 1. It is worth mentioning that, this study found relatively high negative correlation coefficients between *distwces*, *sou_gni*. For example, in the 2014 cross section the correlation coefficient for *distwces* and *sou_gni* was -0.4850.

Table 6). Estimation Results Model 1

Model 1						
Variable	**(Pooled Data)**	**2010**	**2011**	**2012**	**2013**	**2014**
distwces	-.00013092**	-.00012312	-.00020935	-.0001012	-.0001137**	-.0001031
sou_gni	-7.798e-13***	-1.118e-12***	-1.189e-12*	-3.759e-13	-5.389e-13**	-8.693e-13*
des_gni	2.958e-14*	7.140e-14	1.671e-14	6.341e-14**	2.771e-14	1.086e-14
dummy2010	.41723735					

dummy2011	.44131693					
dummy2012	-.46962594					
dummy2013	-.23617658					
_cons	16.893584***	17.330193***	17.805083***	16.076641***	16.491529***	16.87263***
Statistics						
n	1186	163	193	331	275	224
r2	.02145382	.01697863	.02365104	.01234367	.02777063	.02763277

The PPML estimation results for model 2 are described below in Table 7.

Equation 6). Model 2 = *tradevolume* = f(*distwces, sou_gni*, *des_gni, comlang_ethno*)

Model 2 is the studies first augmented model and adds *comlang_ethno* to model 1. The simplest augmented gravity models routinely include measures of cultural affinity such as *comlang_ethno.* If we examine in detail the results from top to bottom, we see that: (i) *distwces* is consistent in sign but not only statistically significant in two configurations; (ii) *sou_gni* is consistent in sign but not statistically significant in all configurations; (iii) *des_gni* is neither consistent in sign nor statistical significant; (iv) *dummy2010* to *dummy2013* remain statistically insignificant; (v) *comlang_ethno* is consistent in sign but not statistically significant in all configurations; (vi) *_cons* is consistent in sign and statistically significant. One again the overall picture in model 2 is similar to that of model 1. There is evidence in favour of a correlation between *sou_gni* and *tradevolume* as well as *comlang_ethno* and *tradevolume;* weak evidence in favour of a correlation between *distwces* and *tradevolume;* and evidence in favour of no correlation between *des_gni* and *tradevolume*. The r2 values of model 2 range between 0.01119545 and 0.09015088 similar to model 1's range of 0.01234367 to 0.02777063. However, by definition r2 will increase with the number of independent variables in the model and does not control for overfitting. Thus, r2 is only a useful statistic to compare models with the same number of variables.

Table 7). Estimation Results Model 2

Model 2						
Variable	**(Pooled Data)**	**2010**	**2011**	**2012**	**2013**	**2014**
distwces	-.0001245**	-.0001142	-.00022314	-.00009441	-.00009613*	-.00008444

sou_gni	-6.476e-13***	-1.049e-12**	-1.123e-12*	-2.944e-13	-3.428e-13*	-6.189e-13
des_gni	6.659e-15	6.529e-14	9.591e-15	2.494e-14	-1.356e-14	-1.695e-14
dummy2010	.33615415					
dummy2011	.55034377					
dummy2012	-.35282149					
dummy2013	-.18080208					
comlang_et~o	1.0742227**	.49605197	.68237557	1.1741608*	1.7602106***	1.5445284**
_cons	16.453368***	17.090007***	17.690799***	15.761599***	15.721214***	16.086696***
Statistics						
n	1186	163	193	331	275	224
r2	.01854397	.01119545	.0182386	.02045531	.09015088	.05583582

The model 3 PPML estimation output is displayed in Table 8 below.

Equation 7). Model 3 = *tradevolume* = f(*distwces, sou_gni*, *des_gni, colony*)

Model 3 is an alternate specification of model 2 that uses *colony* rather than *comlang_ethno*. This specification of the model tries to account for the possible correlation between coronial ties and our narcotics traffic proxy. *Comlang_ethno* and *colony* have a covariance parameter that ranges from 0.7638 in 2011 to 0.5711 in 2012. This is unsurprising as it is common knowledge that colonial ties have had a great impact on the presence of spoken languages. For example, French and English are official languages in Canada because France and the United Kingdom colonized Canada. However, this implies that including both in the same model would lead to issues of autocorrelations.

Model 3 gives a similar picture to that of model 2. For instance: (i) *distwces* is consistent in sign but only statistically significant in two configurations; (ii) *sou_gni* is consistent in sign but not statistically significant in all configurations; (iii) *des_gni* is neither consistent in sign and only statistically significant in one configuration; (iv) *dummy2010* to *dummy2013* remain statistically insignificant; (v) *colony* is consistent in sign but not statistically significant in all configurations; (vi) *_cons* is consistent in sign and statistically significant. Moreover, r2 values of model 2 are similar to those of model 3 with neither model outperforming the other, and both models have identical *n*. Thus this study is indifferent between models 2 and 3.

Table 8). Estimation Results Model 3

Model 3						
Variable	**(Pooled Data)**	**2010**	**2011**	**2012**	**2013**	**2014**
distwces	-.00012944**	-.00012964	-.00020813	-.00009954	-.00011828**	-.00010214
sou_gni	-7.001e-13***	-9.929e-13**	-1.173e-12	-3.335e-13	-4.195e-13*	-8.383e-13
des_gni	1.427e-14	-2.599e-14	1.360e-14	7.047e-14**	3.386e-14	7.253e-15
dummy2010	.43281441					
dummy2011	.42234419					
dummy2012	-.4041065					
dummy2013	-.15022273					
colony	.91996622**	1.1692014	.08305559	1.2674169**	1.7303603***	.33304343
_cons	16.639143***	17.14039***	17.781124***	15.767203***	16.025539***	16.792198***
Statistics						
n	1186	163	193	331	275	224
r2	.01497401	.01130296	.02214922	.02493331	.08858426	.02283491

The PPML estimation results for model 4 are described below in Table 9.

Equation 8). Model 4 = *tradevolume* =

f(*distwces, sou_gni*, *des_gni, comlang_ethno, sou_cy, des_cy*)

Model 4 adds *sou_cy* and destination *des_cy* to model 2 to control for the effect of source and destination country cereal yields on our narcotics traffic proxy. If we examine in detail the results we see that: (i) *distwces* is consistent in sign but only statistically significant in two configurations; (ii) *sou_gni* is consistent in sign but not statistically significant in all configurations; (iii) *des_gni* is inconsistent in sign and not statistically significant in all configurations; (iv) *comlang_ethno* is consistent in sign but only statistically significant in one configuration; (v) *sou_cy* is consistent in sign and statistically significant in all configuration; (vi) *des_cy* is inconsistent in sign and statistically significant in all but two configurations; (vii) *dummy2010* to *dummy2013* remain statistically insignificant; (viii) and *_cons* is consistent in sign and statistically significant. These results would seem to indicate a strong correlation between *tradevolume* and *sou_cy*; weak correlation between *tradevolume* and *sou_gni* as well as *tradevolume* and *des_cy*; weak evidence of no correlation between *tradevolume* and *distwces* as well as *comlang_ethno*; and strong evidence of no correlation between *distwces* and *des_gni*. It is worth noting that *n* is slightly lower for model 4 compared to models 1 through 4.

Table 9). Estimation Results Model 4

Model 4						
Variable	**(Pooled Data)**	**2010**	**2011**	**2012**	**2013**	**2014**
distwces	-.00011596**	-.00010403	-.00017445	-.00009986	-.00010177*	-.00007816
sou_gni	-3.769e-13***	-7.171e-13***	-5.280e-13*	-1.527e-13	-1.275e-13	-3.753e-13
des_gni	1.655e-14	2.726e-14	-3.924e-15	2.656e-14	-2.798e-14	3.207e-14
dummy2010	.3181636					
dummy2011	.43867856					
dummy2012	-.44715797					
dummy2013	-.10972762					
comlang_et~o	.65261626	.69462419	.0313486	.61232478	1.4676558***	.94606918
sou_cy	-.00048526***	-.00030252*	-.00065379**	-.0005236*	-.0003875**	-.00046396***
des_cy	-.00013777***	-.00029376***	-.00017697**	7.889e-06	.00002025	-.00015737*
_cons	18.598014***	19.097418***	20.099377***	17.452225***	16.976243***	18.293277***
Statistics						
n	1175	160	191	328	273	223
r2	.03856474	.02241665	.04651008	.08189414	.13793584	.06481585

And lastly, the PPML estimation results for model 5 are listed below in Table 10.

Equation 10). Model 5 = *tradevolume* =

f(*distwces, sou_gni*, *des_gni, comlang_ethno, sou_cy, des_cy, sou_tpr, des_tpr*)

Model 5 is the complete augmented model with all proposed, non-collinear, control variables. Therefore, model 5 is similar to model 4 with the notable difference being the addition of *sou_tpr* and *des_tpr* as control variables. The estimation results reveal that: (i) *distwces* is neither consistent in sign and only statistically significant in one configuration; (ii) *sou_gni* is consistent in sign but only statistically significant in two configurations; (iii) *des_gni* is inconsistent in sign and statistically insignificant in all configurations; (iv) *comlang_ethno* is consistent in sign and statistically significant in all configurations except 2012; (v) *sou_cy* is inconsistent in sign but not in all configurations; (vi) *des_cy* is consistent in sign but only statistically significant in two configurations; (vii) *sou_tpr* is neither consistent in sign and statistically insignificant in all configuration; (viii) *des_tpr* is inconsistent in sign and only statistically significant in two configuration; (ix) once again *dummy2010 to dummy2013* remain statistically insignificant; (x) and *_cons* is consistent in sign and statistically significant. Therefore, we can read model 5 as indicating evidence of a correlation between *tradevolume* and *comlang_ethno* as well as *sou_cy*; weak evidence in favour of a correlation between *tradevolume* and *distwces*, *sou_gni*, *des_cy* as well as *des_tpr*; and evidence in favour of there being no correlation between *tradevolume* and *des_gni* as well as *tradevolume* and *sou_tpr*. Model 5 has the lowest value of n for all seven models making it, other things equal, less representative. This is due to the number of missing observations for *sou_tpr* and *des_tpr* mentioned in Section 4.1. Furthermore, model 5 has the largest number of variables and is therefore at a greater risk of overfitting the data.

Table 10). Estimation Results Model 5

Model 5						
Variable	**(Pooled Data)**	**2010**	**2011**	**2012**	**2013**	**2014**
distwces	-5.973e-06	.00003982	.000143***	-.00008762	-.00007853	-.0000577
sou_gni	-2.144e-13**	-5.116e-13**	-1.664e-13	-1.568e-13	-1.228e-13	-3.613e-13
des_gni	-2.375e-14	-9.525e-15	-7.069e-14	2.334e-14	-5.000e-14	-3.744e-14
dummy2010	.46072716					
dummy2011	.2347979					
dummy2012	.4876058					
dummy2013	.2860155					
comlang_et~o	1.3768214***	2.1492014***	2.3871211***	.46482017	1.6258882***	1.8398481***
sou_cy	-.00022897*	-.00012865*	-.00012035	-.00043625*	-.00011542	-.00018534*
des_cy	-.0001435*	-.0001721*	-.00012647	-.00012589	-.00009923	-.00022047
sou_tpr	-.00170425	.00015146	-.00253971	-.00317318	-.00141206	.00121602
des_tpr	.00070586	-.00190521	-.00145638	.00179945*	.00482736*	.00198132
_cons	16.516923***	16.474208***	15.688141***	18.147342***	14.607506***	15.157349***
Statistics						
n	833	99	138	285	199	112
r2	.04895827	.11560019	.20569621	.09217903	.09757587	.17193317

4.3 Analysis: Significance and Hypothesizes

Distance: Based on the evidence, we fail to reject the hypothesis that there is no correlation between *tradevolume* and *distwces*. In other words, this study did not find relationship between our weighted distance measure and our narcotics traffic proxy. Of the 30 times that the parameter for *distwces* is estimated in this study it was negative 28 times, and significant 9 times at the 10% level of significance. This result is counterintuitive to the work of authors, such as Allen (2005), who argue that geography plays a role in the competitive advantages of national and international drug producing networks.

Economic Size: We reject the hypothesis that there is no correlation between *tradevolume* and *sou_gni*. In other words, this study found evidence of a correlation between our source country GNI measure and our narcotics traffic proxy. Of the 30 times that the we estimated the parameter for *sou_gni* it was always, negative and significant 17 times at the 10% level of significance. These results are consistent with our hypothesis that the transnational trade of narcotics will be a decreasing function of the source country's economic size. Furthermore, this corroborates the arguments put forward by Castells (2000) and Morrison (1997).

We fail to reject the hypothesis that there is no correlation between *tradevolume* and *des_gni*. In other words, this study did not find a relationship between our destination country GNI measure and our narcotics traffic proxy. Out of the 30 times that the parameter for *des_gni* was estimated, it was positive 20 times and only significant 3 times at the 10% confidence level. This result is somewhat unexpected, and contradicts our hypothesis that the transnational trade of narcotics will be a clear increasing function of the destination country's economic size. Furthermore, this contradicts the quantitative findings of Kahane (2013), but could still coexist with the broader qualitative findings of Chin (2009) and Castells (2000).

Control Variables: This study rejects the hypothesis that there is no correlation between *tradevolume* and *comlang_ethno*. Of the 12 times that the parameter for *comlang_ethno* is estimated in our study it was always positive and statistically significant at the 10% level of significance on 9 occasions. Similarly, this study rejects the hypothesis that there is no correlation between *tradevolume* and *colony*. The parameter for *colony* was estimated six times and was always positive and significant at the 10% level of significance in three cases. An interpretation of this outcome is that there is some evidence for the hypothesized relationship between cultural affinity and our narcotics traffic proxy. This is consistent with Mcillwain's (1999) claim that human relationships and social networks form the basis of organized crime.

We reject the hypothesis that there is no correlation between *tradevolume* and *sou_cy*. In other words, this study did find a relationship between our source country cereal yields measure and our narcotics traffic proxy. Of the 12 estimations of the parameter for *sou_cy* in this study, it was negative in all cases and significant at the 10% level of significance in 10. This would seem to corroborate the hypothesis that individuals in low-income rural areas have a lower opportunity cost of growing illicit drugs. Furthermore, we reject the hypothesis that there is no correlation between *tradevolume* and *des_cy*. In other words, this study did find a decreasing relationship between our destination country cereal yields measure and our narcotics traffic proxy. Of the 12 times that the parameter for *des_cy* was estimated in our analysis it was negative 10 times and statistically significant at the 10% level of significance 6 times. A possible implication, is that as cereal yields increase in destination countries, their demand for narcotic imports decreases. This would seem to allude to different causal mechanisms for the impact of source and destination country cereal yields on the narcotics traffic. These results are consistent with our hypothesis that the transnational trade of narcotics will be a decreasing function of both source and destination country cereal yields. Furthermore, these findings are compatible with the qualitative findings of Felbab-Brown (2006) and Tullis (1987). However, qualitative research into this relationship in high income destination countries could shed light on the underlying mechanisms.

We fail to reject the hypothesis that there is no correlation between *tradevolume* and *sou_tpr*. In other words, this study did not find a relationship between our source country total police personnel measure and our narcotics traffic proxy. Out of the six times the parameter for *sou_tpr* was estimated it was negative four times and never statistically significant at the 10% level of significance. Similarly, we reject the hypothesis that there is a correlation between destination country *tradevolume* and *des_tpr*. In other words, this study did not find a relationship between our destination country law enforcement measure and our narcotics traffic proxy. Out of the six times it was estimated in our analysis the parameter for *des_tpr* was negative four times and only statistically significant twice at the 10% level of significance. This could imply that neither of the two hypothesized law enforcement effects dominates when it comes to the narcotics traffic, further highlighting the indeterminate nature of this relationship raised in Kahane (2013). It is worth noting, however, that Kahane (2013) found that law enforcement activities negatively correlate to the traffic of illegal guns in the United States.

As a side note, the constant was positive and statistically significant and does not have an apparent interpretation given the non-linear nature of the model. Moreover, *dummy2010, dummy2011, dummy2012,* and *dummy2013* in the pooled data configuration of all seven models were never statistically significant. A possible interpretation is that the mechanisms at play are time invariant, that is static, for the five-year period of study when compared to the arbitrary choice of 2014 as the control year. If this result is indeed valid, it further justifies the applicability of pooled time series and cross-sectional analysis compared with time series and true panel analysis.

Chapter 5: Conclusions

5.1 Overview of Study: Method, Evidence and Significance

The specific research question was, “are distance and economic size correlated with the volume of narcotics traffic between countries”? To which our hypothesis was, for countries where the narcotics traffic is present, distance and economic size are correlated with the volume of narcotics traffic between countries. The results of the PPML estimations for the various data configurations and model specifications presented in chapter 4 do seem to tentatively reject this hypothesis. In other words, although our narcotics traffic proxy does appear positively correlated with one of our economic size measures, it does not appear inversely correlated with our weighted distance measure. Furthermore, the low explanatory power of the models, represented in the r2 estimation statistics, implies that there are other important factors at play in the transnational narcotics traffic. In other words, assuming that the present study is valid, that is that the data is sound and the methods are credible, the classic and augmented gravity models provide a weak explanation for the pattern of transnational narcotics traffic. The following sections will summarize the study's method, examine the pooled data configuration of model 6 as an example of the findings, discuss these results in terms of the interdisciplinary literature and examine future lines of theoretical and empirical enquiry.

This study defined globalization as a dynamic and ongoing expansion of trade networks and economic activities at a global scale. The transnational narcotics traffic is dynamic (UNODC, 2017), relies on trade networks (Asad & Harris, 2003) and is an economic activity (Umprimny, 1996). Therefore, by definition the transnational narcotics traffic is a globalization issue. Furthermore, this study interpreted international development as the process of achieving certain specific and general social and economic goals to better the human condition. Authors, such as Robins (2016), Thoumi (2013), Astorga (2013), Chin (2009) and Perl (2001), have written extensively on the impact of the narcotics traffic on international development and their consensus is that the narcotics traffic is a significant obstacle to international development. In particular in low and middle-income countries such as Afghanistan, Colombia, Mexico, Myanmar and Yemen.

This study's model was the gravity model of international trade. This model demonstrates desirable conceptual and practical traits such as focusing on bilateral trade (Anderson & Van-Wincoop, 2003) and being empirically robust (Head & Mayer, 2014). The secondary data for this study was a convenience sample drawn from the UNODC's (2016) IDS, the CEPII's (2016) GeoDist and World Bank's (2016) World Development Indicators. Open source data, such as these databases, offer both opportunities and challenges for quantitative studies into the narcotics traffic. Furthermore, unit standardization posed a unique challenge for this study, as the narcotics seizure data in the UNODC's (2016) IDS dataset was reported in different forms and measures. This study used a novel "dose" approach to unit standardization using the leading toxicology and pharmacology literature on narcotic doses.

The nature of the UNODC's (2016) IDS database for 2010 to 2014 limited the possible data configuration to cross sections. Nonetheless, this study also advanced an alternate pooled time series data configuration to account for possible dynamic processes (Sayrs, 1989). Traditional estimation methods such as OLS have shortcomings when estimating the gravity model. Thus, this study chose the PPML estimator because it provides parameters in the original scale (Cox et al., 2008), does not require the definition of ln (0) (Gourieroux et al., 1984), and allows the assumption of homoscedasticity to be relaxed (Silva & Tenreyro, 2006).

This study calculated the detailed summary statistics for the dependent variable as well as the complete set of proposed independent and control variables. The initial data analysis of the narcotics traffic proxy (*tradevolume)* was promising with adequate sample sizes and approximately log-normal distributions. The samples for the independent and control variables also had an adequate number of observations, that is, more than the 30 observation rule of thumb for cross-sectional analysis. Interestingly, the sample distribution of weighted distance (*distwces)* was bimodal and left skewed. In addition, the sample distributions of source country GNI (*sou_gni*) and destination country GNI (*des_gni*) were left skewed.

This study proposed a core specification of the gravity model (model 1) as well as four augmented specifications (models 2 to 5) to control for omitted variable bias. Model 1 provides a useful baseline for our study but likely suffer from omitted variable bias. Models 2 and 3 incorporate measures of cultural affinity to model 1 but are still probably under-fitted. Model 4 includes a measure of cereal yield and arguably demonstrate the best fit. Model 5 is the complete augmented model, yet it has the lowest number of observations (29.76% fewer observations when compared to model 1) and there is a chance that it is over-fitting the data. Thus, model 4 is the study's preferred models and we will use it to underpin this study's conclusions.

Table 11 below provides a convenient summary of model 4's estimates for the study period. The variables are listed under the *variable*'s column, the configuration under which the variable demonstrated a negative correlation is listed under *Negative Correlation* and the configuration under which the variable demonstrated a positive correlation is listed under *Positive Correlation.* As before, one star is equal to the significance at the 10% confidence level, two stars are equal significance at the 5% confidence level and three stars are equal to the significance at the 1% confidence level.

Table 11). Summary of Model 4's Estimates

Variable	Negative Correlation	Positive Correlation
distwces	Pooled**, 2010, 2011, 2012, 2013*, 2014	
sou_gni	Pooled***, 2010***, 2011*, 2012, 2013, 2014	
des_gni	2011, 2013	Pooled, 2010, 2012, 2014
comlang_ethno		Pooled, 2010, 2011, 2012, 2013***, 2014
sou_cy	Pooled***, 2010*, 2011**, 2012*, 2013**, 2014***	
des_cy	Pooled***, 2010***, 2011**, 2014*	2012, 2013
_cons		Pooled***, 2010***,2011***, 2012***, 2013***, 2014***

Reading Table 11 above, we see that the sign of the PPML estimations coefficients for model 4 are as hypothesized and consistent across data configurations, the notable exceptions being *des_gni* in 2011 and 2013 as well as *des_cy* in 2012 and 2013. The strongest evidence in terms of statistical significance is for the correlation between *tradevolume* and *sou_cy*, *des*_cy as well as *_cons*. These control variables are statistically significant at the 10% level of significance in four or more of the six configurations for model 1. There is also evidence in terms of statistical significance for the correlation between *tradevolume* and *sou_gni,* with this variable being statistically significant, at the 10% level of significance, in three of six configurations. The weakest evidence in terms of statistical significance is for the correlation between *tradevolume* and *distwces, des_gni* as well as *comlang_ethno* these variable being statistically significant, at the 10% level of significance, in two or fewer configurations.

5.2 Implications: Link to the Interdisciplinary Literature

This study's tentative rejection of the application of the gravity model to the narcotics traffic, would seem to contradict the tendency in economics to see the narcotics traffic as any other global market. At 0.03856474 the r2 for the model 4 pooled data configuration implies that our independent variables only explain approximately 3.86% of the variation in the dependent variable. In other words, distance and economic size likely have a limited impact on the transnational traffic of narcotics. This would imply that other economic factors beside the market are at play, such as the role of institutions noted by Asad and Harris (2003) and Thoumi (2003). However, the pooled data estimation of model 4 conforms to our understanding of the gravity model with some minor adjustments, notably to the expected sign of the exporting courtiers economic size. This finding is broadly consistent with authors, such as Albertson and Fox (2012) and Umprimny (1996), who argue for the cautious application of economic principles to the narcotics market.

The estimation results do not provide convincing evidence that, in countries where narcotics seizures are reported to the UNODC, narcotics imports decrease with the distance between countries. This could imply that the logistical barriers faced by growing global trafficking networks, described in Robins (2016), are more complex than distance. However, the observed negative correlation between narcotics seizures reported to the UNODC and source country GNI corroborates some aspects of the narcotics traffic observed in the qualitative literature. For instance, Asad and Harris (2003) observed that the narcotics trafficking areas of Afghanistan and Pakistan share similar attributes, such as economic vulnerability, which this study may be capturing. Yet, this study did not find a systematic relationship between destination country GNI and narcotics seizures reported to the UNODC. This is counterintuitive as authors, such as Castells (2000), argue that narcotics will generally flow to markets able to afford them.

This study's results highlight that the presence of a common language, or colonial link, between trafficking partners is correlated with increases in both exports and imports of narcotics. These cultural affinities could be capturing the social arrangements favourable to the narcotics production described by Thoumi (2003). Moreover, the estimation results seem to indicate that, in source countries where narcotics seizures are reported to the UNODC, increases in cereal yields will reduce narcotics exports. Similarly, in destination country's imports would also appear to decrease with cereal yields. This negative correlation between cereal yields and narcotics exports may be illustrating the low opportunity cost of narcotics production observed by Tullis (1987) in the Andes. Nevertheless, this study did not find any notable relationship between narcotics seizures reported to the UNODC and total police personnel. Again, this could be due to the variables competing deterrence and detection effects noted by Kahane (2013).

5.3 Limitations: The Study and Future Leads

There is an important caveat to the conclusion discussed above, and that is that this study's results are contingent on the strength of our proxies as well as our theoretical framework. Furthermore, some of the inconsistent findings may reflect the inherent difficulty in quantifying the narcotics traffic as well as the limited available data. For instance, the large number of missing observations for the source and destination country total police personnel variable noted in section 4.1. Hence the following section will discuss the prospects for future studies such as the addition of alternate control variables, the redefinition of proxies, the disaggregation of certain variables and the possibilities of competing theoretical frameworks.

A theme found in the writing of authors such as Kelly & et al. (2005) and Allen (2005) is the idea that the forces driving the increase in the flow of goods, services, capital and information between nation states are simultaneously increasing the volume of the narcotics traffic. As the existing measure of licit bilateral trade flows, such as the CEPII (2017)'s Gravity dataset, do not include the narcotics traffic, it would be possible to include such a measure to our model to control for this effect. Another possible control variable would be a measure of institutional strength, such as Transparency International's (2017) Corruption Perceptions Index. Such a variable could cater to the argument that the narcotics traffic is idiosyncratic and that institutions are likely the biggest economic factor at play. This is the position taken by authors, such as Asad and Harris (2003) and Thoumi (2003), who argue that a country's competitive advantage in the production of narcotics stems from weak institutional contexts.

In future studies it may also be useful to include a measure of development in the model as it could be a leading factor in the transnational narcotics traffic. For instance, there is qualitative evidence that poverty and economic insecurity have contributed to the rise of opium cultivation, in Burma, Afghanistan, and parts of China (Morrison, 1997). Specifically, future studies could use a transformation of the United Nations Development Programme's (UNDP) human development index (HDI) to replace GNI in some specifications of the gravity model. The HDI includes a national income, education, and health component and is a useful measure of development as it takes a broader capability approach than traditional measures such as GNI (UNDP, 2016; World Bank, 2016).

An alternate specification of the studies proxy for the volume of the narcotics traffic that may be worth examining, is the number of seizures between pairs of countries reported in the UNODC's (2016) IDS dataset. Instinctively, we would expect that greater trade in illicit drugs would not only imply large shipments, but also more shipments. Thus, if countries A and B had three seizures and countries X and Y had thirty seizures, it may be fair to assume that there was more trade between X and Y than between A and B. This would be a conceptually simpler proxy and would conveniently side-step issues related to units and substances. However, it would treat very large and very small seizures as equivalent.

A competing framework to the gravity model worth exploring is the new economic geography model. Unlike other economic theories of trade, gravity model included, the new economic geography attempts not only to explain why countries with similar attributes have similar trade patterns, but also why countries with similar attributes do not have similar trade patterns (Ottaviano & Puga, 1998). Economic activities, including the production of narcotics, are not equally distributed over space, and although economic, social and institutional factors provide useful answers they fail to account for this. For example, Thoumi (2003) finds that narcotics producing countries share similar economic, social, institutional and geographic factors, yet not all countries that demonstrate these factors produce narcotics. By centring, the level of analysis on the decisions of firms and workers to concentrate in certain areas the new economic geography provides a way to interpret these counterintuitive findings (Ottaviano & Puga, 1998). Furthermore, even though Leamer and Levinsohn (1995) are strong proponents of the gravity model and of the importance of distance to international trade, they acknowledge that Krugman's method in the new economic geography offers a nuanced approach to modelling the impact of geography. Moreover, the new economic geography provides a novel way to look at dynamic changes in global comparative advantages (Ottaviano & Puga, 1998). This could corroborate the importance that qualitative studies such as Kelly et al. (2005) and Allen (2005) have placed on globalization as a catalyst for the transnational narcotics traffic.

Motivated by the importance of the narcotics traffic to our understanding of globalization and international development, this study set out to seize an opportunity for novel quantitative research. This study tentatively rejects its hypothesis that, for countries where the narcotics traffic in present, distance and economic size are correlated with the volume of narcotics traffic between countries. However, it is important to note that this is an exploratory study that raises more questions than it answers. Therefore, although some of the study's results are encouraging, it would be wise to revisit the data and explore the implications of other theoretical frameworks.

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Annex

6.1 Ethics: Statistics and Econometrics

The Committee on Professional Ethics of the American Statistical Association (1999) states that "it is important that all statistical practitioners recognize their potential impact on the broader society and the attendant ethical obligations to perform their work responsibly" (Executive Summary). This is especially true given that "statistics play a vital role in many aspects of science, the economy, governance, and even entertainment" (Committee on Professional Ethics of the American Statistical Association, 1999, Executive Summary). The Committee on Professional Ethics of the American Statistical Association (1999) also underlines the fact that statistical analysis can have a profound impact on social and economic policy.

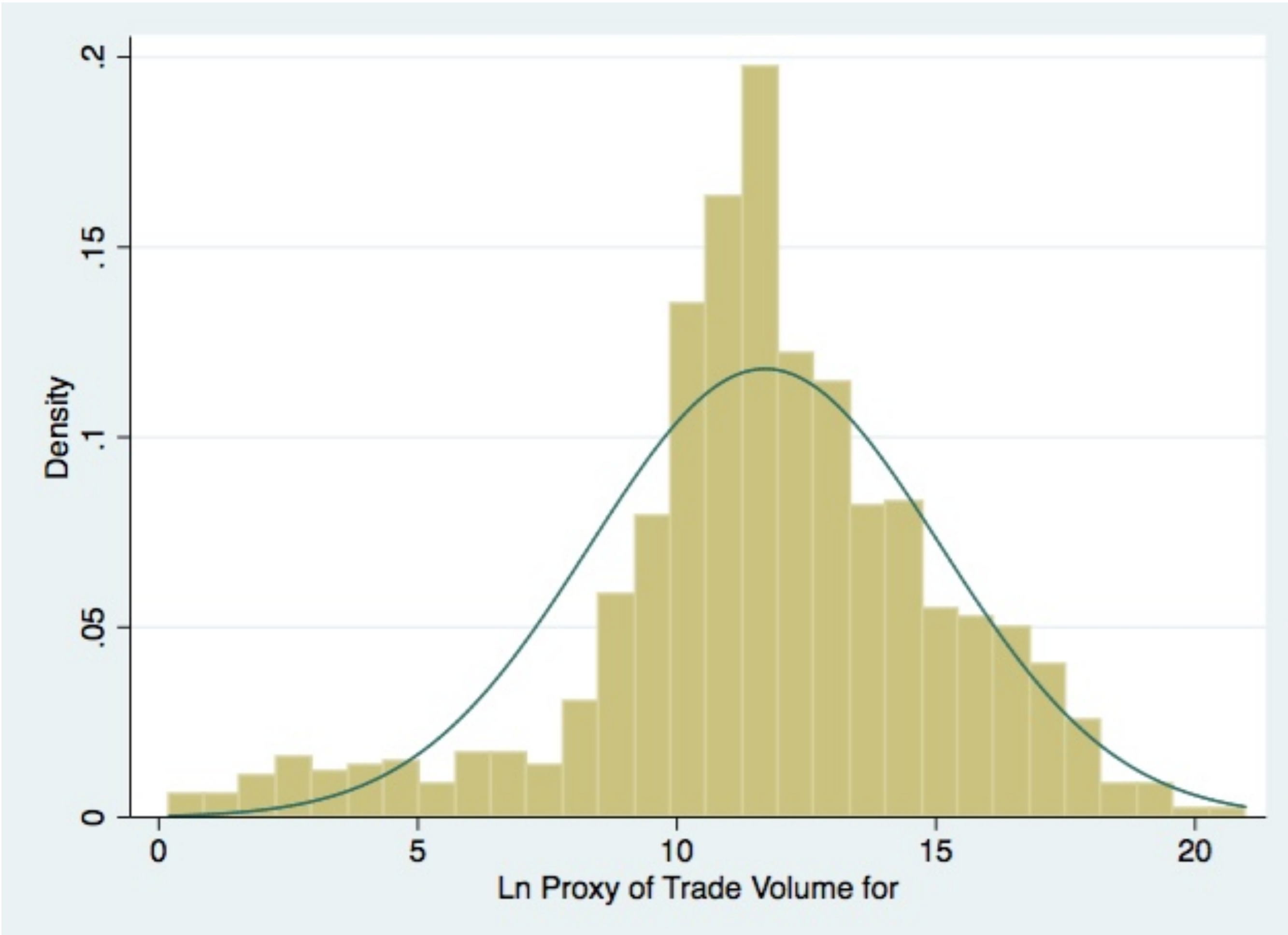
However, unlike in statistics, econometrics does not have a code of professional ethics (Levy and Peart, 2008). This is surprising given that ethical issues do exist in econometrics. For example, an econometric researcher could bias his results by strategically choosing his variables and estimation methods to obtain estimators that corroborate the desired results. This is especially problematic when the econometrics researcher is a paid consultant, given that in such a case, it is safe to assume that seeking the truth is no longer his only incentive. A possible solution to this ethical issue would be to encourage greater transparency in econometric research. In their article, Levy and Peart (2008), demonstrate how, even under ideal market conditions, transparency in econometric consulting may not prevail. Therefore, Levy and Peart (2008) recommend that a code of professional ethics be adopted in econometrics and encourage greater transparency in research.

Given the lack of an econometric professional ethics code, this study strove to follow the Ethical Guidelines for Statistical Practice put forward by the Committee on Professional Ethics of the American Statistical Association (1999). Although principally aimed at statisticians, the Committee on

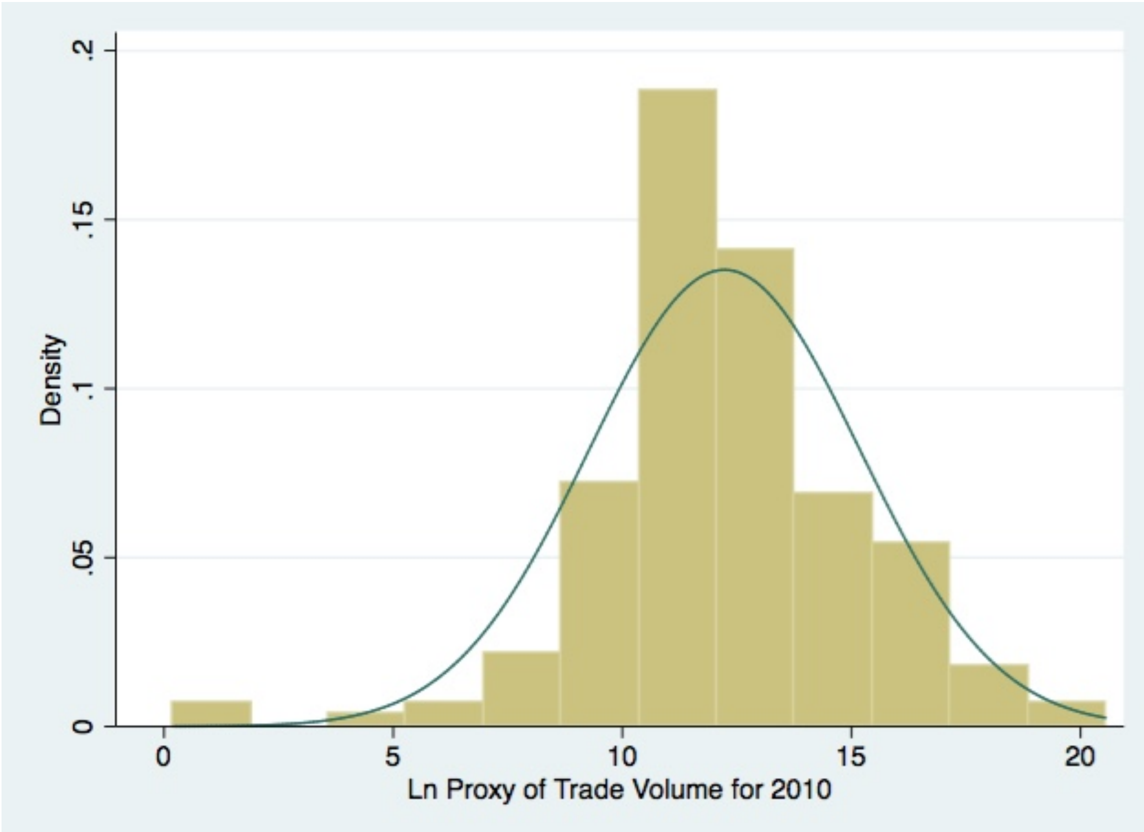
Professional Ethics of the American Statistical Association (1999) argues that the principles of its Ethical Guidelines for Statistical Practice pertain to all fields that use statistics. This study adhered to these guidelines and general principles. Specifically, to avoid ethical pitfalls, this study took steps to: take into account the value of research into the underground economy; accepted the consequences of errors and mistakes made in good faith; refrained from systematically favouring a predetermined outcome; conducted research in a scientific manner; complied with all relevant laws; stayed up to date with best practices. Concretely, this implied staying up to date on relevant publications, keeping sensitive data secure, being open with methods, being transparent with assumptions, and refraining from overstating the scope or validity of the conclusions. For example, this study favoured transparency by citing all data, explaining all methods, defining all models and highlighting all assumptions.

Consent and permission for the data used did not pose a problem given that the World Bank's (2015) World Development Indicators Database and the United Nations Office on Drugs and Crime (2015) Drug Trafficking Statistics are open for public access, download and use. Those who collected the information are unlikely to object to how the research used the data, given that these observations were freely available to encourage a greater understanding of the social world. The data that the research used does not raise privacy issues given the high level of aggregation. To illustrate, it would be virtually impossible to single out a specific individual from the total volume of drug seizures in a given country in a given year. The data used were aggregate, passively generated data, as such individual consent was a nonissue.

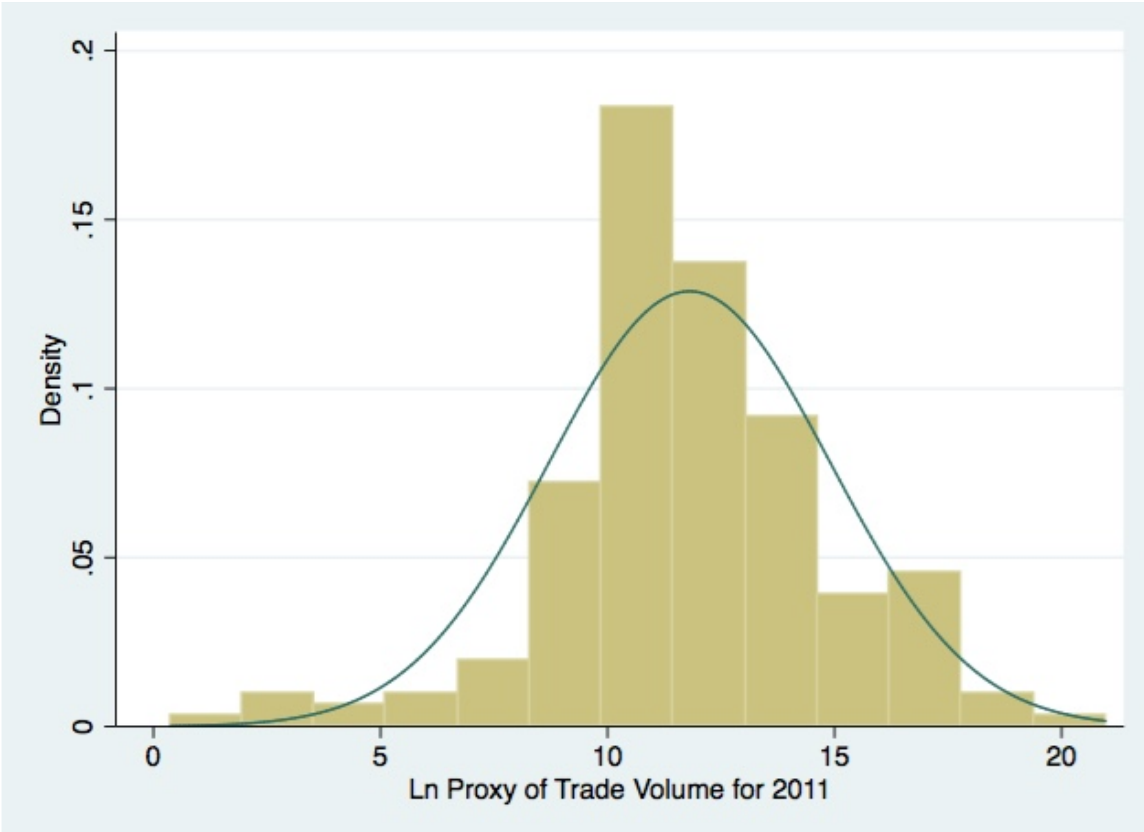
Graph 1). Histogram of Ln Narcotics Seizures (*tradevolume*)



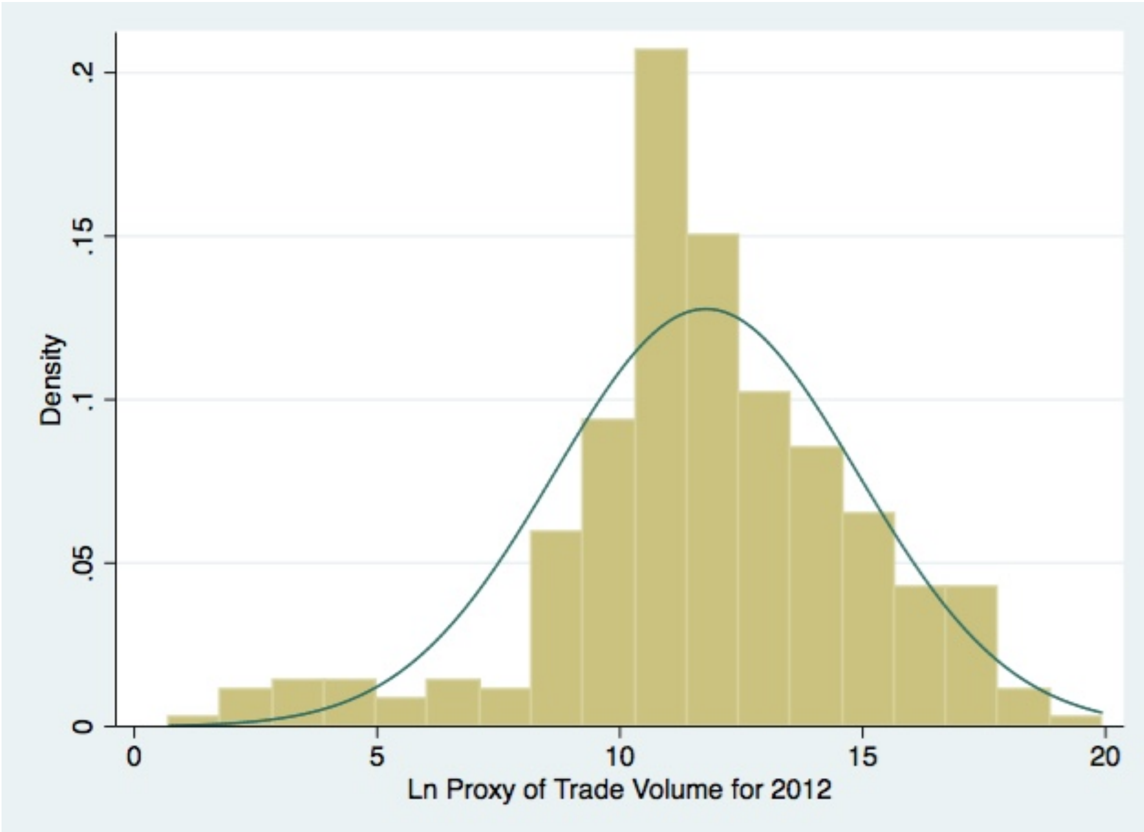
Graph 2). Histogram of Ln Narcotics Seizures 2010 (*tradevolume2010*)



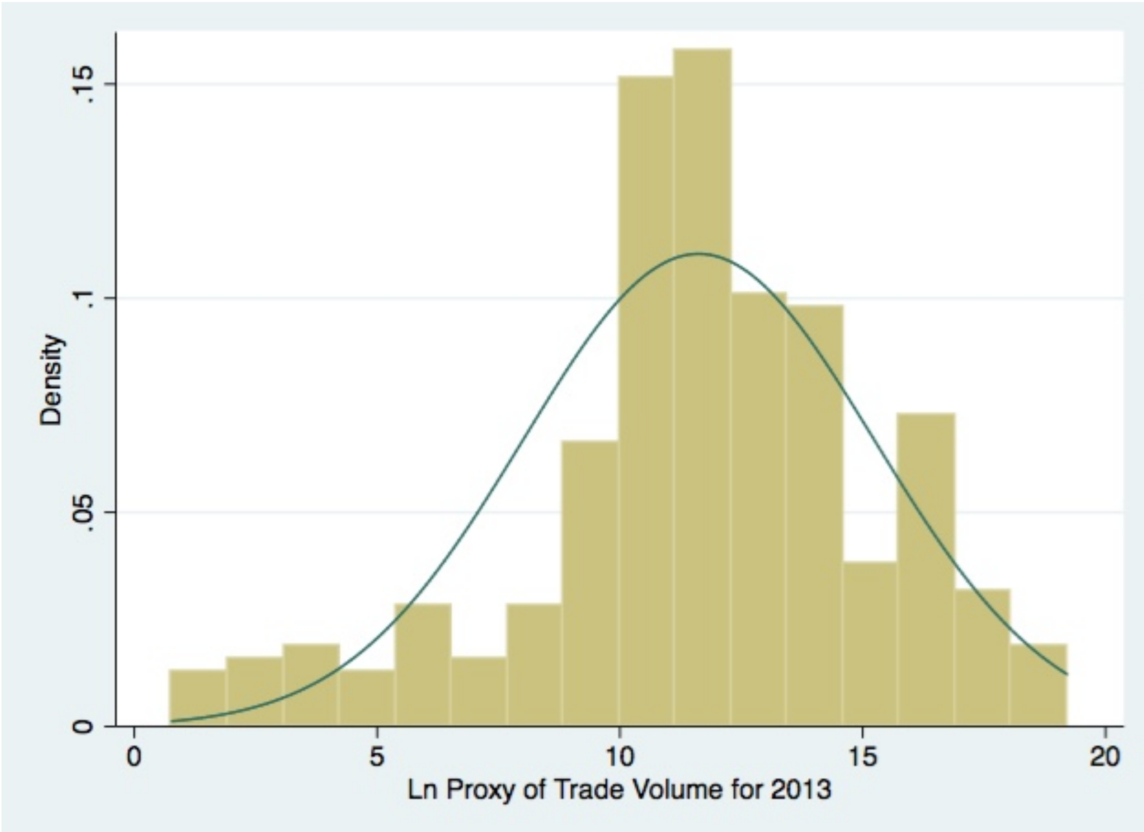
Graph 3). Histogram of Ln Narcotics Seizures 2011 (*tradevolume2011*)



Graph 4). Histogram of Ln Narcotics Seizures 2012 (*tradevolume2012*)



Graph 5). Histogram of Ln Narcotics Seizures 2013 (*tradevolume2013*)



Graph 6). Histogram of Ln Narcotics Seizures 2014 (*tradevolume2014*)

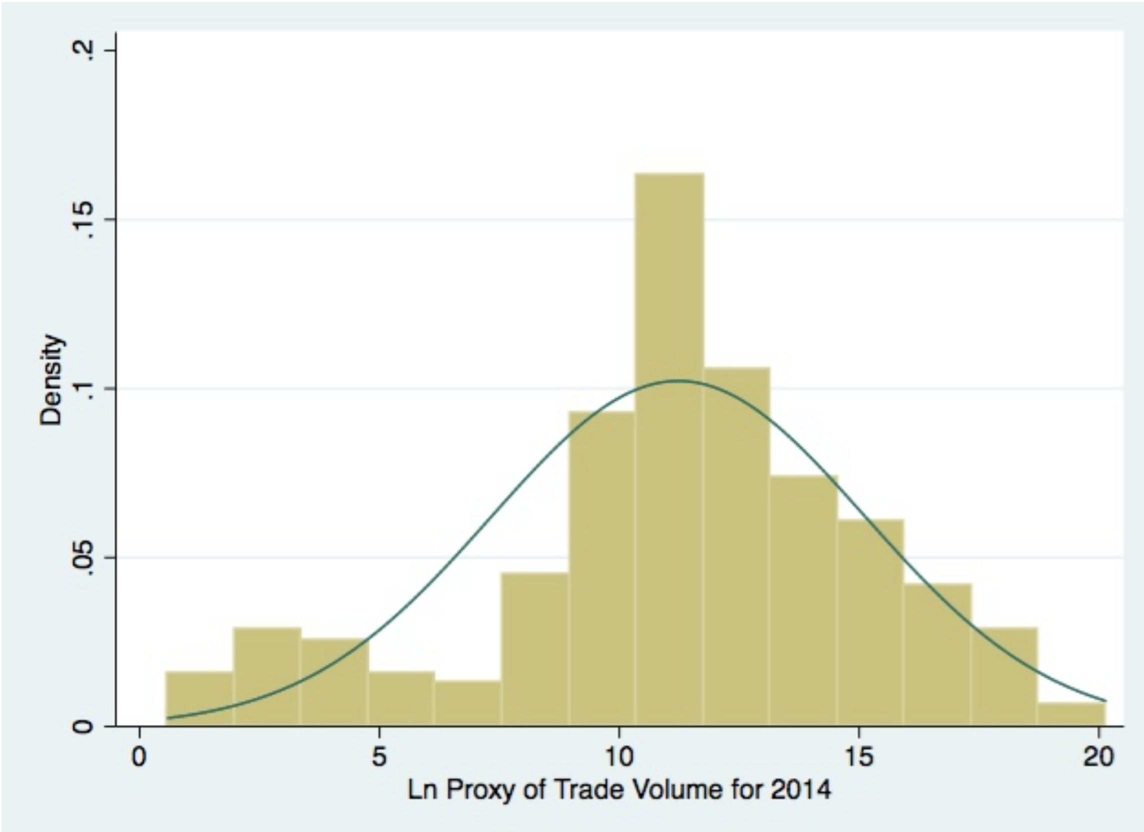


Table 12). Summary Statistics Weighted Distance (*distwces*)

Weighted Distance (Set to -1)				
	Percentiles	Smallest		
1%	231.2235	123.2928		
5%	556.2308	174.622		
10%	817.1057	174.8092	Obs	1,186
25%	1550.527	188.3535	Sum of Wgt.	1,186
50%	5186.63		Mean	5538.797
		Largest	Std. Dev.	4141.839
75%	9111.224	17776.66		
90%	10739.91	17985.13	Variance	1.72e+07
95%	11655.91	18297.72	Skewness	.2894516
99%	14759.13	19067.9	Kurtosis	1.827892

Graph 7). Histogram Weighted Distance (*distwces*)

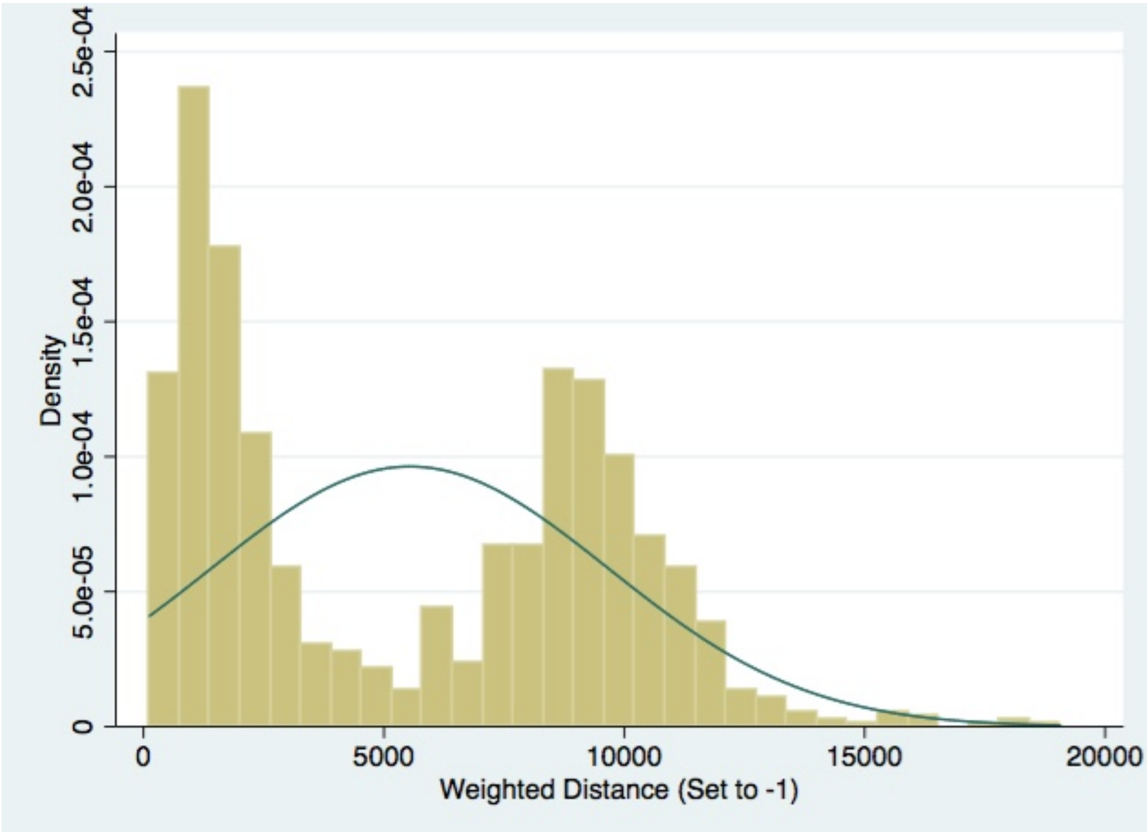


Table 13). Summary Statistics Source Country GNI (*sou_gni*)

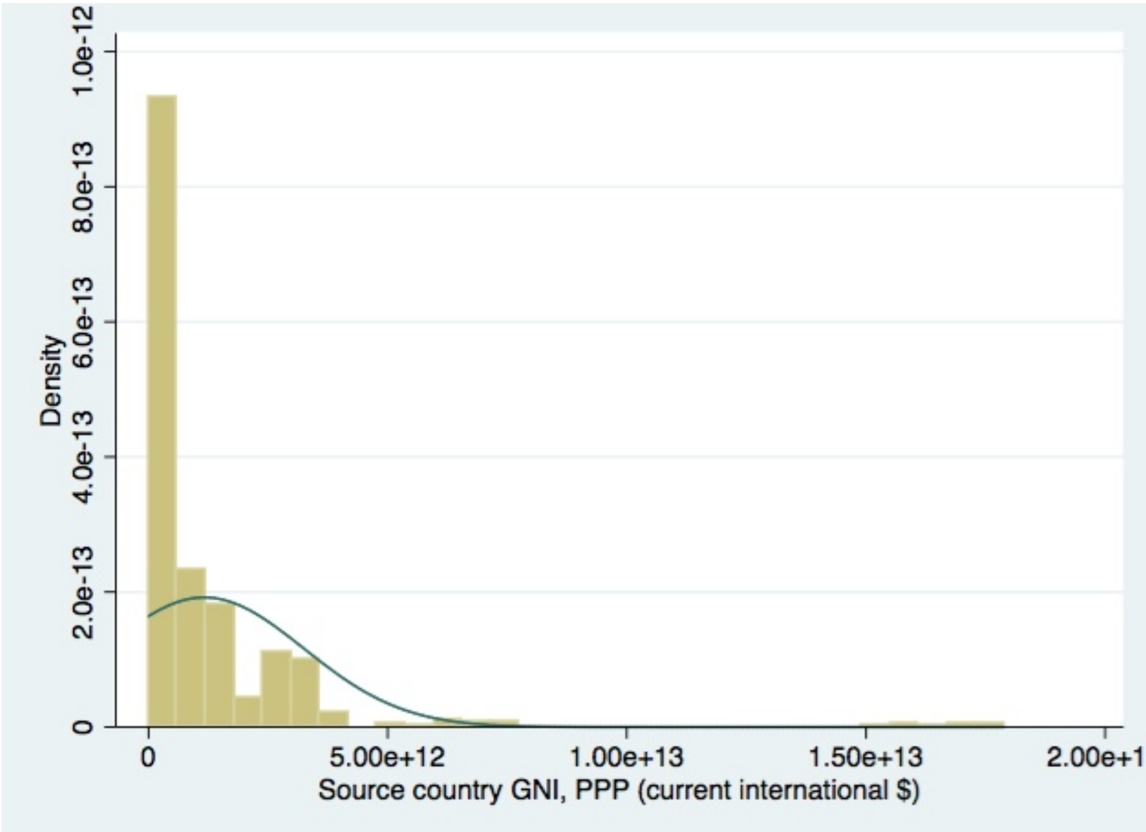
Source Country GNI , PPP (current international $)					Source Country GNI , PPP (current international $) [2010]					Source Country GNI , PPP (current international $) [2011]				
_	Percentiles	Smallest				Percentiles	Smallest				Percentiles	Smallest		
1%	8.92e+09	1.04e+09			1%	1.04e+09	1.04e+09			1%	8.92e+09	2.92e+09		
5%	4.04e+10	1.04e+09			5%	1.48e+10	1.04e+09			5%	5.37e+10	8.92e+09		
10%	5.37e+10	1.04e+09	Obs	1,186	10%	4.30e+10	1.04e+09	Obs	163	10%	5.95e+10	1.61e+10	Obs	193
25%	1.17e+11	1.09e+09	Sum of Wgt.	1,186	25%	6.90e+10	1.09e+09	Sum of Wgt.	163	25%	1.12e+11	4.48e+10	Sum of Wgt.	193
50%	4.36e+11		Mean	1.17e+12	50%	3.38e+11		Mean	9.47e+11	50%	4.73e+11		Mean	1.28e+12
		Largest	Std. Dev.	2.08e+12			Largest	Std. Dev.	1.59e+12			Largest	Std. Dev.	2.17e+12
75%	1.51e+12	1.71e+13			75%	1.33e+12	5.25e+12			75%	1.90e+12	5.73e+12		
90%	3.02e+12	1.79e+13	Variance	4.32e+24	90%	2.72e+12	5.25e+12	Variance	2.51e+24	90%	2.90e+12	1.58e+13	Variance	4.71e+24
95%	3.51e+12	1.79e+13	Skewness	5.040824	95%	2.72e+12	5.25e+12	Skewness	5.042933	95%	3.37e+12	1.58e+13	Skewness	4.789697
99%	1.58e+13	1.79e+13	Kurtosis	36.24736	99%	5.25e+12	1.51e+13	Kurtosis	41.34334	99%	1.58e+13	1.58e+13	Kurtosis	31.68928
Source Country GNI , PPP (current international $) [2012]					Source Country GNI , PPP (current international $) [2013]					Source Country GNI , PPP (current international $) [2014]				
	Percentiles	Smallest				Percentiles	Smallest				Percentiles	Smallest		
1%	2.29e+10	3.00e+09			1%	2.57e+10	1.04e+10			1%	2.38e+10	4.67e+09		
5%	3.34e+10	4.92e+09			5%	4.57e+10	2.30e+10			5%	3.67e+10	1.38e+10		
10%	5.68e+10	9.52e+09	Obs	331	10%	5.19e+10	2.57e+10	Obs	275	10%	6.90e+10	2.38e+10	Obs	224
25%	1.14e+11	2.29e+10	Sum of Wgt.	331	25%	1.18e+11	2.84e+10	Sum of Wgt.	275	25%	1.80e+11	2.76e+10	Sum of Wgt.	224
50%	3.56e+11		Mean	1.02e+12	50%	3.62e+11		Mean	1.24e+12	50%	6.19e+11		Mean	1.36e+12
		Largest	Std. Dev.	1.75e+12			Largest	Std. Dev.	2.34e+12			Largest	Std. Dev.	2.39e+12
75%	1.49e+12	6.14e+12			75%	1.51e+12	1.71e+13			75%	1.56e+12	7.26e+12		
90%	3.02e+12	6.14e+12	Variance	3.06e+24	90%	3.19e+12	1.71e+13	Variance	5.48e+24	90%	3.24e+12	1.79e+13	Variance	5.70e+24
95%	3.58e+12	1.66e+13	Skewness	5.017967	95%	3.73e+12	1.71e+13	Skewness	4.819857	95%	3.90e+12	1.79e+13	Skewness	4.829402
99%	6.14e+12	1.66e+13	Kurtosis	40.21039	99%	1.71e+13	1.71e+13	Kurtosis	31.4361	99%	1.79e+13	1.79e+13	Kurtosis	32.0177

Table 14). Summary Statistics Destination Country GNI (*des_gni*)

Destination country GNI , PPP (current international $)					**Destination country GNI , PPP (current international $) [2010]**					**Destination country GNI , PPP (current international $) [2011]**				
	Percentiles	Smallest				Percentiles	Smallest				Percentiles	Smallest		
1%	1.02e+10	1.04e+09			1%	1.09e+09	1.04e+09			1%	1.68e+10	2.92e+09		
5%	3.53e+10	1.09e+09			5%	1.56e+10	1.09e+09			5%	2.82e+10	1.68e+10		
10%	1.05e+11	2.74e+09	Obs	1,186	10%	3.87e+10	2.74e+09	Obs	163	10%	1.12e+11	2.08e+10	Obs	193
25%	2.81e+11	2.92e+09	Sum of Wgt.	1,186	25%	2.80e+11	4.41e+09	Sum of Wgt.	163	25%	2.79e+11	2.08e+10	Sum of Wgt.	193
50%	8.24e+11		Mean	1.51e+12	50%	7.47e+11		Mean	1.32e+12	50%	7.83e+11		Mean	1.52e+12
		Largest	Std. Dev.	2.25e+12			Largest	Std. Dev.	1.85e+12			Largest	Std. Dev.	2.39e+12
75%	2.17e+12	1.79e+13			75%	2.08e+12	4.60e+12			75%	2.15e+12	1.58e+13		
90%	3.58e+12	1.79e+13	Variance	5.06e+24	90%	2.39e+12	5.25e+12	Variance	3.43e+24	90%	3.37e+12	1.58e+13	Variance	5.71e+24
95%	3.64e+12	1.79e+13	Skewness	4.814979	95%	2.84e+12	1.51e+13	Skewness	5.199208	95%	3.37e+12	1.58e+13	Skewness	4.510222
99%	1.66e+13	1.79e+13	Kurtosis	32.58914	99%	1.51e+13	1.51e+13	Kurtosis	38.66667	99%	1.58e+13	1.58e+13	Kurtosis	26.91779
Destination country GNI , PPP (current international $) [2012]					**Destination country GNI , PPP (current international $) [2013]**					**Destination country GNI , PPP (current international $) [2014]**				
	Percentiles	Smallest				Percentiles	Smallest				Percentiles	Smallest		
1%	2.19e+10	9.52e+09			1%	2.52e+10	3.10e+09			1%	1.23e+10	3.12e+09		
5%	3.74e+10	1.19e+10			5%	5.19e+10	1.27e+10			5%	3.67e+10	8.50e+09		
10%	1.05e+11	2.19e+10	Obs	331	10%	1.18e+11	2.52e+10	Obs	275	10%	9.13e+10	1.23e+10	Obs	224
25%	2.56e+11	2.19e+10	Sum of Wgt.	331	25%	3.01e+11	2.52e+10	Sum of Wgt.	275	25%	2.94e+11	2.38e+10	Sum of Wgt.	224
50%	4.66e+11		Mean	1.29e+12	50%	1.51e+12		Mean	1.63e+12	50%	1.02e+12		Mean	1.82e+12
		Largest	Std. Dev.	2.05e+12			Largest	Std. Dev.	2.06e+12			Largest	Std. Dev.	2.80e+12
75%	2.15e+12	1.66e+13			75%	2.17e+12	6.63e+12			75%	2.71e+12	1.79e+13		
90%	3.02e+12	1.66e+13	Variance	4.19e+24	90%	3.64e+12	1.71e+13	Variance	4.24e+24	90%	3.60e+12	1.79e+13	Variance	7.85e+24
95%	3.58e+12	1.66e+13	Skewness	5.209078	95%	3.73e+12	1.71e+13	Skewness	4.735085	95%	3.90e+12	1.79e+13	Skewness	4.272112
99%	1.66e+13	1.66e+13	Kurtosis	38.39541	99%	1.71e+13	1.71e+13	Kurtosis	35.17086	99%	1.79e+13	1.79e+13	Kurtosis	24.55366
Destination country GNI , PPP (current international $)					**Destination country GNI , PPP (current international $) [2010]**					**Destination country GNI , PPP (current international $) [2011]**				
	Percentiles	Smallest				Percentiles	Smallest				Percentiles	Smallest		
1%	1.02e+10	1.04e+09			1%	1.09e+09	1.04e+09			1%	1.68e+10	2.92e+09		
5%	3.53e+10	1.09e+09			5%	1.56e+10	1.09e+09			5%	2.82e+10	1.68e+10		
10%	1.05e+11	2.74e+09	Obs	1,186	10%	3.87e+10	2.74e+09	Obs	163	10%	1.12e+11	2.08e+10	Obs	193
25%	2.81e+11	2.92e+09	Sum of Wgt.	1,186	25%	2.80e+11	4.41e+09	Sum of Wgt.	163	25%	2.79e+11	2.08e+10	Sum of Wgt.	193

50%	8.24e+11		Mean	1.51e+12	50%	7.47e+11		Mean	1.32e+12	50%	7.83e+11		Mean	1.52e+12
		Largest	Std. Dev.	2.25e+12			Largest	Std. Dev.	1.85e+12			Largest	Std. Dev.	2.39e+12
75%	2.17e+12	1.79e+13			75%	2.08e+12	4.60e+12			75%	2.15e+12	1.58e+13		
90%	3.58e+12	1.79e+13	Variance	5.06e+24	90%	2.39e+12	5.25e+12	Variance	3.43e+24	90%	3.37e+12	1.58e+13	Variance	5.71e+24
95%	3.64e+12	1.79e+13	Skewness	4.814979	95%	2.84e+12	1.51e+13	Skewness	5.199208	95%	3.37e+12	1.58e+13	Skewness	4.510222
99%	1.66e+13	1.79e+13	Kurtosis	32.58914	99%	1.51e+13	1.51e+13	Kurtosis	38.66667	99%	1.58e+13	1.58e+13	Kurtosis	26.91779
Destination country GNI , PPP (current international $) [2012]					**Destination country GNI , PPP (current international $) [2013]**					**Destination country GNI , PPP (current international $) [2014]**				
	Percentiles	Smallest				Percentiles	Smallest				Percentiles	Smallest		
1%	2.19e+10	9.52e+09			1%	2.52e+10	3.10e+09			1%	1.23e+10	3.12e+09		
5%	3.74e+10	1.19e+10			5%	5.19e+10	1.27e+10			5%	3.67e+10	8.50e+09		
10%	1.05e+11	2.19e+10	Obs	331	10%	1.18e+11	2.52e+10	Obs	275	10%	9.13e+10	1.23e+10	Obs	224
25%	2.56e+11	2.19e+10	Sum of Wgt.	331	25%	3.01e+11	2.52e+10	Sum of Wgt.	275	25%	2.94e+11	2.38e+10	Sum of Wgt.	224
50%	4.66e+11		Mean	1.29e+12	50%	1.51e+12		Mean	1.63e+12	50%	1.02e+12		Mean	1.82e+12
		Largest	Std. Dev.	2.05e+12			Largest	Std. Dev.	2.06e+12			Largest	Std. Dev.	2.80e+12
75%	2.15e+12	1.66e+13			75%	2.17e+12	6.63e+12			75%	2.71e+12	1.79e+13		
90%	3.02e+12	1.66e+13	Variance	4.19e+24	90%	3.64e+12	1.71e+13	Variance	4.24e+24	90%	3.60e+12	1.79e+13	Variance	7.85e+24
95%	3.58e+12	1.66e+13	Skewness	5.209078	95%	3.73e+12	1.71e+13	Skewness	4.735085	95%	3.90e+12	1.79e+13	Skewness	4.272112
99%	1.66e+13	1.66e+13	Kurtosis	38.39541	99%	1.71e+13	1.71e+13	Kurtosis	35.17086	99%	1.79e+13	1.79e+13	Kurtosis	24.55366

Graph 8). Histogram Source Country GNI (*sou_gni*)



Graph 9). Histogram Destination Country GNI (*des_gni*)

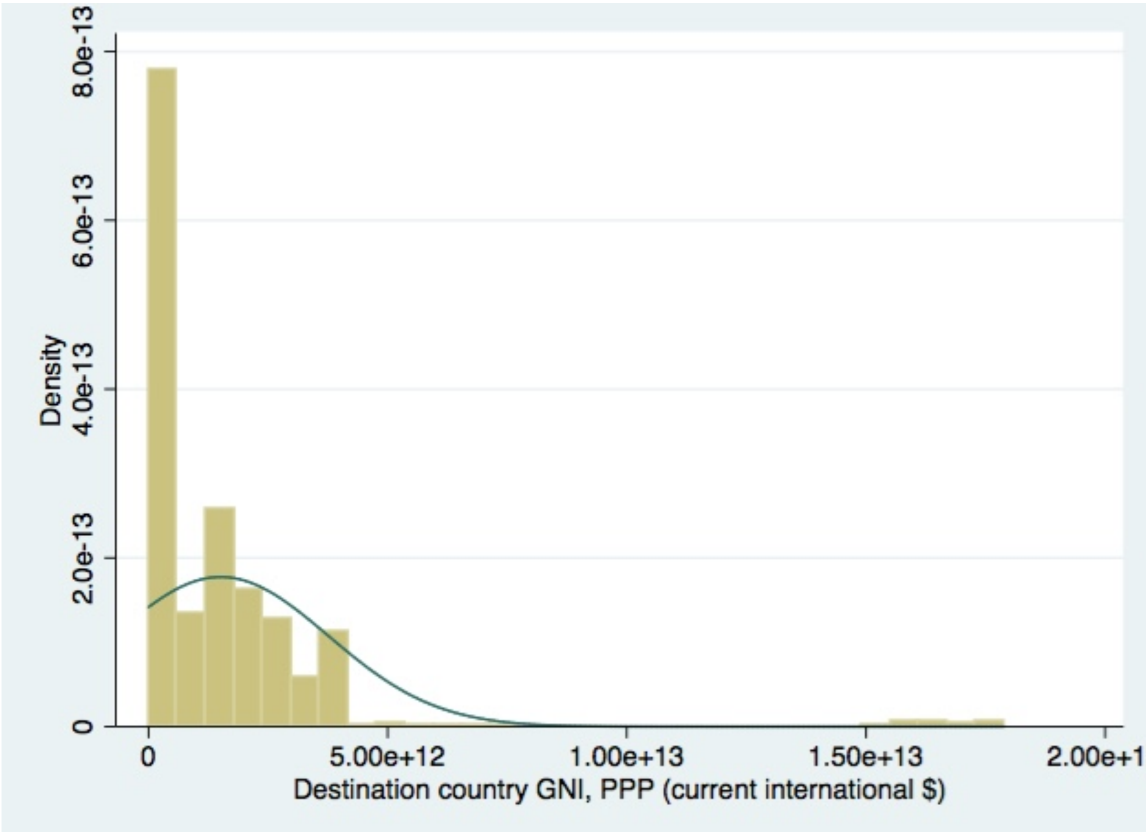


Table 15). Summary Statistics Cultural Affinity (*comlang_ethno* & *colony*)

Common Language (Spoken)			Colonial Link		
Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
1,186	.1804384	.3847145	1,186	.1281619	.334411

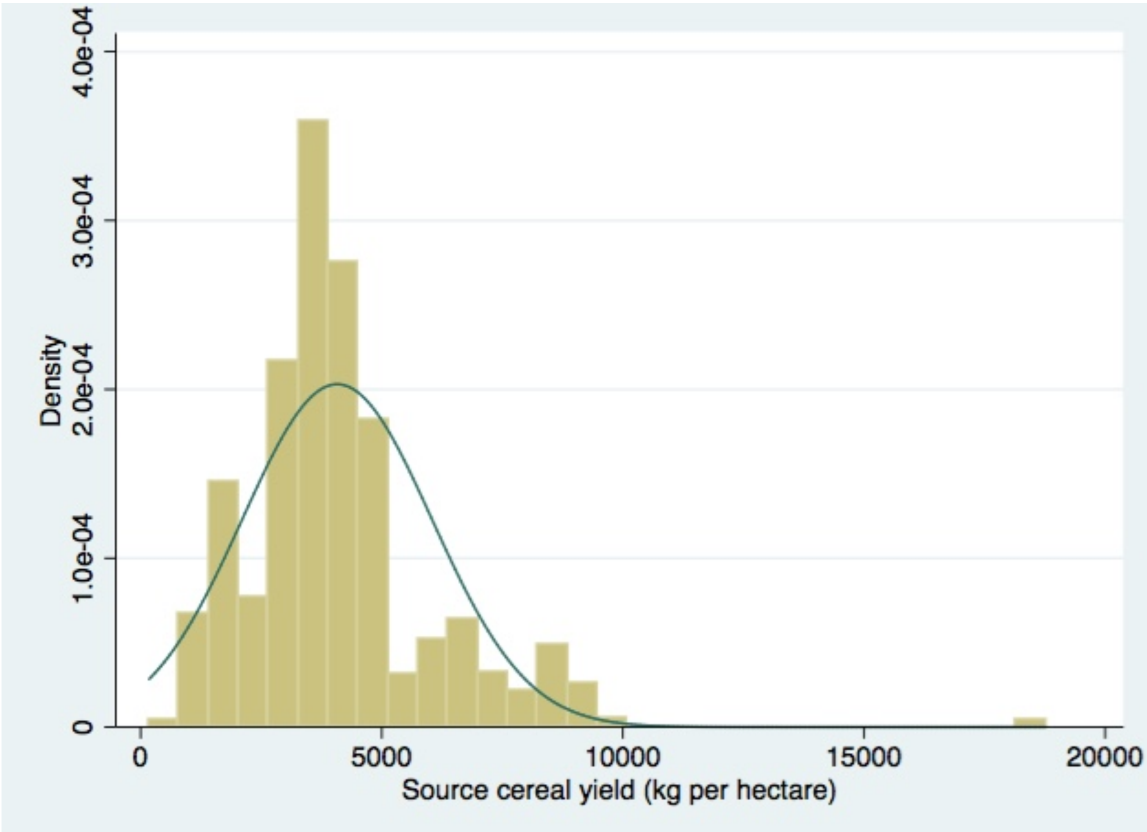
Table 16). Summary Statistics Source Country Cereal Yield (*sou_cy*)

Source country cereal yield (kg per hectare)					Source country cereal yield (kg per hectare) [2010]					Source country cereal yield (kg per hectare) [2011]				
	Percentiles	Smallest				Percentiles	Smallest				Percentiles	Smallest		
1%	1016.6	177.8			1%	860.9	804.1			1%	1334.8	177.8		
5%	1454.4	196.2			5%	1547.5	860.9			5%	1614.4	1334.8		
10%	1744.8	762	Obs	1,178	10%	1547.5	1196.2	Obs	161	10%	1614.4	1337.9	Obs	191
25%	3010	804.1	Sum of Wgt.	1,178	25%	2676.4	1196.2	Sum of Wgt.	161	25%	3187	1337.9	Sum of Wgt.	191
50%	3737.1		Mean	4074.099	50%	3769.6		Mean	4025.257	50%	3707.8		Mean	4029.481
		Largest	Std. Dev.	1965.147			Largest	Std. Dev.	2614.501			Largest	Std. Dev.	1778.962
75%	4640.5	9539			75%	4956.8	9348.1			75%	4504.5	9009		
90%	6913.2	18774.2	Variance	3861802	90%	6718.4	18774.2	Variance	6835616	90%	6620.7	9009	Variance	3164706
95%	8545	18774.2	Skewness	1.747823	95%	8569.3	18774.2	Skewness	3.482604	95%	7800.8	9009	Skewness	.7462061
99%	9212.5	18774.2	Kurtosis	10.72647	99%	18774.2	18774.2	Kurtosis	19.72841	99%	9009	9009	Kurtosis	3.305194
Source country cereal yield (kg per hectare) [2012]					**Source country cereal yield (kg per hectare) [2013]**					**Source country cereal yield (kg per hectare) [2014]**				
	Percentiles	Smallest				Percentiles	Smallest				Percentiles	Smallest		
1%	1016.6	196.2			1%	1236.4	1165.1			1%	1345.8	1139		
5%	1401.2	762			5%	1652	1236.4			5%	1454.4	1172.6		
10%	1644.3	1016.6	Obs	329	10%	1828.4	1236.4	Obs	274	10%	1938	1345.8	Obs	223
25%	2990.5	1016.6	Sum of Wgt.	329	25%	3264.8	1236.4	Sum of Wgt.	274	25%	3253.2	1378.4	Sum of Wgt.	223
50%	3696.7		Mean	3952.826	50%	4056.35		Mean	4133.96	50%	3726.5		Mean	4252.942
		Largest	Std. Dev.	1831.545			Largest	Std. Dev.	1765.699			Largest	Std. Dev.	1996.852
75%	4584.5	8666.3			75%	4826.4	9212.5			75%	4892.6	9539		
90%	6309.7	8666.3	Variance	3354555	90%	7079.3	9212.5	Variance	3117693	90%	7637.4	9539	Variance	3987417
95%	8545	8666.3	Skewness	.9038967	95%	7340.4	9212.5	Skewness	.8810481	95%	9073.7	9539	Skewness	.9944766
99%	8666.3	8666.3	Kurtosis	3.787092	99%	9212.5	9212.5	Kurtosis	3.757088	99%	9539	9539	Kurtosis	3.55943

Table 17). Summary Statistics Destination Country Cereal Yield (*des_cy*)

Destination country cereal yield (kg per hectare)					Destination country cereal yield (kg per hectare) [2010]					Destination country cereal yield (kg per hectare) [2011]				
	Percentiles	Smallest				Percentiles	Smallest				Percentiles	Smallest		
1%	1016.6	35.7			1%	373.6	220			1%	452.3	177.8		
5%	1723.8	177.8			5%	1723.8	373.6			5%	1614.4	452.3		
10%	2240.3	182.3	Obs	1,183	10%	1842.7	860.9	Obs	162	10%	2259.4	1337.9	Obs	193
25%	3256.7	217.6	Sum of Wgt.	1,183	25%	3303.7	1298.7	Sum of Wgt.	162	25%	3436.7	1337.9	Sum of Wgt.	193
50%	4437.9		Mean	4811.522	50%	4571.35		Mean	4879.855	50%	4016		Mean	4740.097
		Largest	Std. Dev.	2167.659			Largest	Std. Dev.	2440.831			Largest	Std. Dev.	2077.819
75%	6271.6	9539			75%	6722.1	9348.1			75%	6620.7	9009		
90%	7637.4	9539	Variance	4698745	90%	8569.3	9348.1	Variance	5957655	90%	7800.8	9009	Variance	4317333
95%	8630.1	18774.2	Skewness	.8712077	95%	8569.3	9348.1	Skewness	1.274062	95%	9009	9009	Skewness	.3226321
99%	9348.1	21844.7	Kurtosis	6.610583	99%	9348.1	18774.2	Kurtosis	7.932642	99%	9009	9009	Kurtosis	2.299689
Destination country cereal yield (kg per hectare) [2012]					Destination country cereal yield (kg per hectare) [2013]					Destination country cereal yield (kg per hectare) [2014]				
	Percentiles	Smallest				Percentiles	Smallest				Percentiles	Smallest		
1%	1016.6	367.2			1%	1236.4	182.3			1%	1172.6	35.7		
5%	1858.4	1016.6			5%	2081.6	217.6			5%	1455.4	1139		
10%	2172.45	1016.6	Obs	330	10%	2240.3	1236.4	Obs	274	10%	2137.2	1172.6	Obs	224
25%	3035.7	1016.6	Sum of Wgt.	330	25%	4031.4	1236.4	Sum of Wgt.	274	25%	2831.1	1378.4	Sum of Wgt.	224
50%	4203.8		Mean	4649.197	50%	4831.5		Mean	4968.835	50%	4437.9		Mean	4870.356
		Largest	Std. Dev.	1908.646			Largest	Std. Dev.	1945.636			Largest	Std. Dev.	2607.208
75%	6215	8666.3			75%	6065.7	9212.5			75%	7173	9539		
90%	7523.8	8666.3	Variance	3642928	90%	7318	9212.5	Variance	3785499	90%	8050.3	9539	Variance	6797532
95%	8545	8666.3	Skewness	.3341278	95%	8630.1	9212.5	Skewness	.2161195	95%	9073.7	9539	Skewness	1.412248
99%	8666.3	8666.3	Kurtosis	2.447236	99%	9212.5	9212.5	Kurtosis	2.639705	99%	9539	21844.7	Kurtosis	9.3602

Graph 10). Histogram Source Country Cereal Yield (*sou_cy*)



Graph 11). Histogram Destination Country Cereal Yield 2011 (*des_cy*)

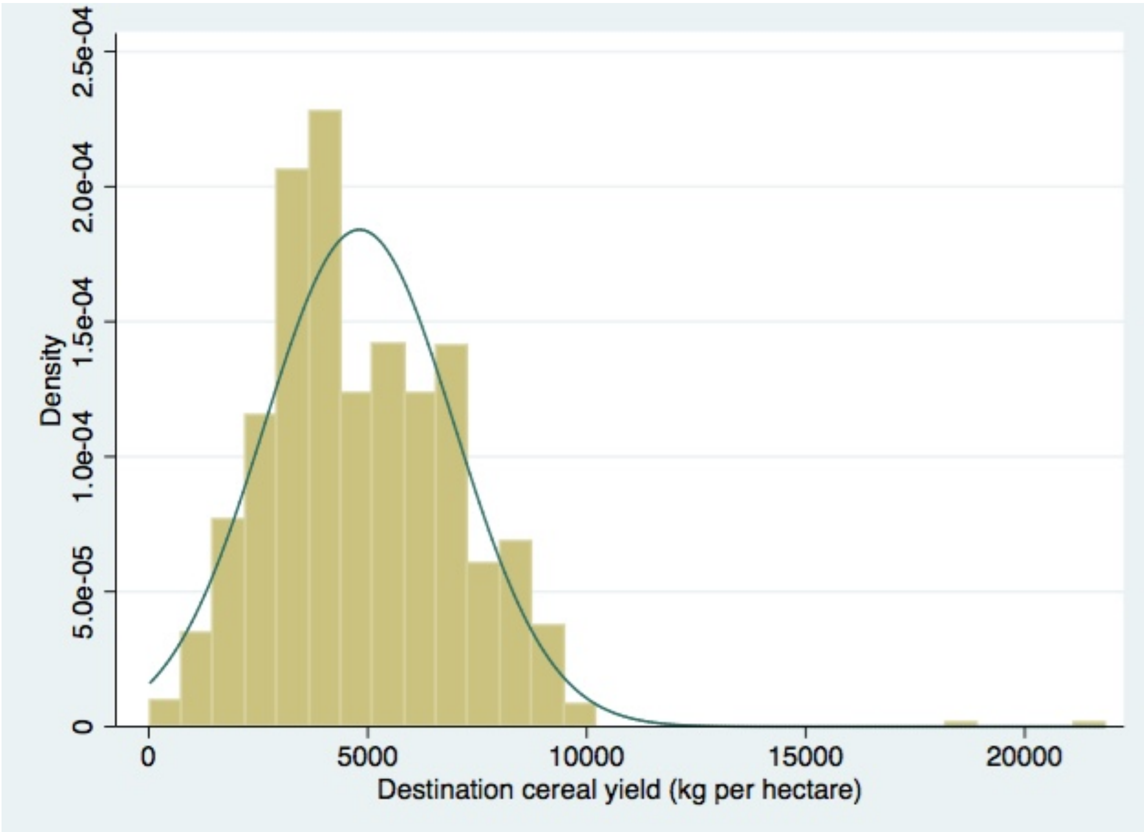


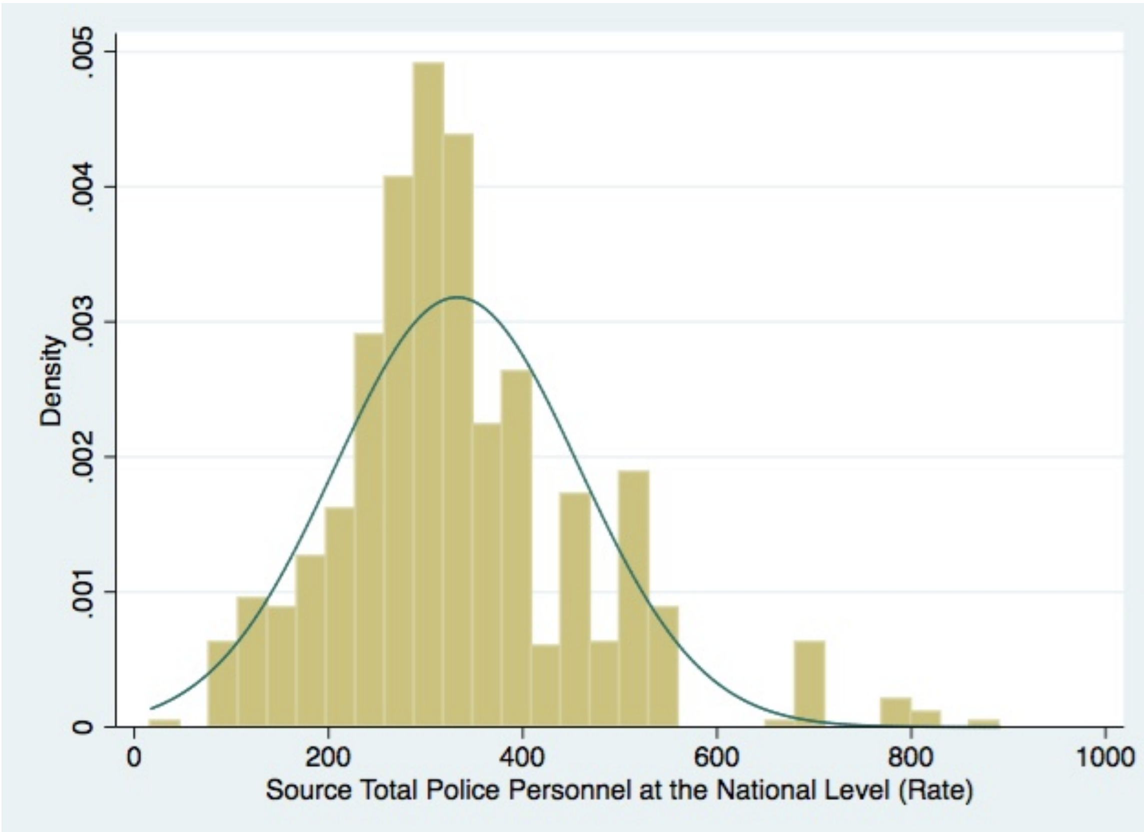
Table 18). Summary Statistics Source Country Total Police Personnel (*sou_tpr*)

Source Country Total Police Personnel at the National Level (Rate)					Source Country Total Police Personnel at the National Level (Rate) [2010]					Source Country Total Police Personnel at the National Level (Rate) [2011]				
	Percentiles	Smallest				Percentiles	Smallest				Percentiles	Smallest		
1%	86.3	17.3			1%	128.4	100.9			1%	95.9	86.7		
5%	138.7	84.5			5%	138.7	128.4			5%	194.9	95.9		
10%	192.8	84.5	Obs	948	10%	138.7	128.4	Obs	111	10%	238.7	111.4	Obs	154
25%	258.6	86.3	Sum of Wgt.	948	25%	246.6	128.4	Sum of Wgt.	111	25%	257.4	111.4	Sum of Wgt.	154
50%	315.8		Mean	332.2807	50%	309.1		Mean	323.6919	50%	315.8		Mean	329.3805
		Largest	Std. Dev.	125.43			Largest	Std. Dev.	145.1642			Largest	Std. Dev.	102.7423
75%	384.3	812.3			75%	383.1	812.3			75%	387.7	692.1		
90%	519.9	812.3	Variance	15732.7	90%	459.7	812.3	Variance	21072.66	90%	454	692.1	Variance	10555.97
95%	530.6	812.3	Skewness	.9164838	95%	527.4	812.3	Skewness	1.357139	95%	504	692.1	Skewness	.969127
99%	774.9	891.3	Kurtosis	4.828749	99%	812.3	891.3	Kurtosis	6.478658	99%	692.1	692.1	Kurtosis	5.668119
Source Country Total Police Personnel at the National Level (Rate) [2012]					**Source Country Total Police Personnel at the National Level (Rate) [2013]**					**Source Country Total Police Personnel at the National Level (Rate) [2014]**				
	Percentiles	Smallest				Percentiles	Smallest				Percentiles	Smallest		
1%	86.3	86.3			1%	84.5	17.3			1%	192.6	87.4		
5%	132.5	86.3			5%	135.3	84.5			5%	196.6	192.6		
10%	169.7	86.3	Obs	310	10%	196.6	84.5	Obs	223	10%	264.85	192.6	Obs	150
25%	240.7	86.3	Sum of Wgt.	310	25%	258.6	96.5	Sum of Wgt.	223	25%	305	192.6	Sum of Wgt.	150
50%	319.3		Mean	327.1927	50%	307		Mean	320.4561	50%	320.4		Mean	369.7087
		Largest	Std. Dev.	131.6003			Largest	Std. Dev.	114.9386			Largest	Std. Dev.	127.5141
75%	384.3	681.6			75%	369.1	530.6			75%	444.2	708.9		
90%	504.9	774.9	Variance	17318.63	90%	485.7	530.6	Variance	13210.89	90%	526.2	794.9	Variance	16259.84
95%	551.5	774.9	Skewness	.8952646	95%	530.6	530.6	Skewness	.283071	95%	526.2	794.9	Skewness	1.144226
99%	681.6	774.9	Kurtosis	4.276984	99%	530.6	673.2	Kurtosis	2.836953	99%	794.9	794.9	Kurtosis	4.433819

Table 19). Summary Statistics Destination Country Total Police Personnel (*des_tpr*)

Destination Country Total Police Personnel at the National Level (Rate)					Destination Country Total Police Personnel at the National Level (Rate) [2010]					Destination Country Total Police Personnel at the National Level (Rate) [2011]				
	Percentiles	Smallest				Percentiles	Smallest				Percentiles	Smallest		
1%	86.3	84.5			1%	138.7	128.4			1%	133.1	86.7		
5%	158.2	84.5			5%	214.6	138.7			5%	157	133.1		
10%	208.3	84.5	Obs	1,053	10%	219.8	199.7	Obs	148	10%	215.6	133.1	Obs	177
25%	299.1	84.5	Sum of Wgt.	1,053	25%	299.1	199.9	Sum of Wgt.	148	25%	291.7	150.5	Sum of Wgt.	177
50%	369.1		Mean	369.7085	50%	383.1		Mean	389.9667	50%	370.6		Mean	364.7047
		Largest	Std. Dev.	124.5101			Largest	Std. Dev.	136.1497			Largest	Std. Dev.	126.5768
75%	463.3	884.5			75%	447.9	884.5			75%	454	692.1		
90%	522.3	884.5	Variance	15502.77	90%	527.4	884.5	Variance	18536.73	90%	521.6	854.6	Variance	16021.68
95%	530.6	884.5	Skewness	.2355535	95%	544.7	884.5	Skewness	1.592601	95%	521.6	854.6	Skewness	.7707152
99%	692.1	891.3	Kurtosis	4.132829	99%	884.5	891.3	Kurtosis	7.328504	99%	854.6	854.6	Kurtosis	5.295613
Destination Country Total Police Personnel at the National Level (Rate) [2012]					**Destination Country Total Police Personnel at the National Level (Rate) [2013]**					**Destination Country Total Police Personnel at the National Level (Rate) [2014]**				
	Percentiles	Smallest				Percentiles	Smallest				Percentiles	Smallest		
1%	86.3	86.3			1%	84.5	84.5			1%	187.6	187.6		
5%	132.5	86.3			5%	140.8	84.5			5%	196.6	187.6		
10%	169.7	86.3	Obs	307	10%	207.3	84.5	Obs	250	10%	273.8	192.6	Obs	171
25%	249.5	86.3	Sum of Wgt.	307	25%	304.2	84.5	Sum of Wgt.	250	25%	320.4	192.6	Sum of Wgt.	171
50%	339.7		Mean	340.7909	50%	367.5		Mean	373.2884	50%	423.8		Mean	404.0368
		Largest	Std. Dev.	118.9623			Largest	Std. Dev.	123.9443			Largest	Std. Dev.	110.6635
75%	446.3	521			75%	462.6	530.6			75%	522.3	526.2		
90%	466	521	Variance	14152.04	90%	530.6	530.6	Variance	15362.18	90%	526.2	526.2	Variance	12246.41
95%	521	551.5	Skewness	-.2311246	95%	530.6	530.6	Skewness	-.4259498	95%	526.2	526.2	Skewness	-.2979072
99%	521	774.9	Kurtosis	2.733604	99%	530.6	530.6	Kurtosis	2.373911	99%	526.2	526.2	Kurtosis	1.751415

Graph 12). Histogram Source Country Total Police Personnel (*sou_tpr*)



Graph 13). Histogram Destination Country Total Police Personnel (*des_tpr*)