A Quantitative Application of Enterprise and Social Embeddedness Theories to the Transnational Trafficking of Cocaine in Europe

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Abstract

Illegal enterprise and social embeddedness theories have highlighted the importance of market forces and social factors, respectively, for analyzing organized crime and organized criminal activities. This paper empirically demonstrates the joint explanatory power of these respective theories in the case of the transnational trafficking of cocaine. It does so by conceptualizing transnational cocaine trafficking as a network of relationships among countries; a network whose structure reflects the actions of manifold organized criminal groups. The analysis utilizes exponential random graph models to analyze quantitative data on cocaine trafficking which are ordinarily difficult to capture in empirical research. The analysis presented focuses on a set of 36 European countries. The results yield insights into the nature of the relationship among economic incentives, social ties, geographic features and corruption, and how, in turn, this relationship influences the structure of the transnational cocaine network and the modi operandi *of cocaine traffickers.*

Keywords

Enterprise theory; Social embeddedness; Cocaine trafficking; Social Network Analysis; Exponential Random Graph Models

Introduction

Scholars invariably adopt two main theories to interpret organized and transnational crime. The first of them is illegal enterprise theory—developed by Schelling (1967), Smith (1971, 1975), and later by Reuter (1983)— which conceptualizes organized crime as an "economic activity that happens to be illegal" (Liddick 1999, 404). According to this theory, offenders are rational decision-makers who decide to supply illicit commodities and services simply because it is profitable to do so (Levi 2008; Reuter 1983). The second approach is social embeddedness theory, which was introduced into the criminological debate by van de Bunt and Kleemans (1999) and Morselli (2005), and which contends that the majority of organized criminal activities are embedded in social relations. These scholars maintain that focusing solely on the economic aspect is to neglect an integral component of the dynamics of criminal organizations (Kleemans 2013). Whilst these two theories have distinct foci, they are not necessarily in opposition to one another; in fact, they are expedient for understanding different aspects of the complexity of organized crime.

Despite the widespread adoption of illegal enterprise and social embeddedness theories and the persistence of debates concerning their validity for interpreting organized crime and complex criminal activities—such as transnational drug trafficking— there is still a relative dearth of empirical evidence on their explanatory power, especially at the macro level (Kleemans 2013; Paoli 2014). More generally, "[c]riminologists too often ignore issues of co-offending and complex criminal activities, as these are difficult to capture in empirical research. Co-offending and complex criminal activities are very close to the core of organized crime research, and there is no reason why criminologists should ignore such issues" (Kleemans 2014, 49). In light of this gap in criminological research, our study empirically applies the conceptual apparatus of the illegal enterprise and social embeddedness theories in order to explain the structure of transnational cocaine trafficking within Europe. The trafficking of cocaine from South America to Europe requires some degree of organization and, as such, it is primarily undertaken by criminal organizations (see, for example, Calderoni 2012; Calderoni et al. 2016; von Lampe 2016; Zaitch 2002).

The aim of this study is to demonstrate quantitatively the joint explanatory power of illegal enterprise and social embeddedness theories at the macro level by integrating prior contributions that have already tested organized crime theories principally at the micro level (e.g., Bruinsma and Bernasco, 2004; Kleemans and de Poot, 2008; McGloin and Povitsky Stickle, 2011; Reiss and Farrington, 1991). It accordingly develops an approach able to test extant theories of organized crime empirically, while simultaneously considering the transnational activities which, today, form a crucial component of much organized crime (Edwards and Gill 2003; McCarthy 2011; von Lampe 2016). Moreover, the study explains why certain trafficking routes are favored over others. In this regard, our analysis expands current knowledge on the determinants of the structure of transnational drug trafficking by considering cocaine across the whole of Europe, whereas previous studies on drug trafficking have concentrated on heroin, whose countries of origin are different (e.g., Berlusconi et al. 2017; Chandra and Barkell 2013;

Giommoni et al. 2017), examined a smaller or different geographical scope (e.g., Chandra and Joba 2015a; Chandra et al. 2014), or simply concentrated on different research questions and analytical techniques (e.g., Boivin 2013). Shifting and expanding the scope of our analysis makes it possible to discern crucial differences in the mechanisms governing different illicit markets in different macro contexts.

The paper is structured as follows. The next section provides an overview of illegal enterprise and social embeddedness theories and delineates our research hypotheses. Section two sets out our analytical framework. The third section presents and discusses our results, first by focusing on the structure of transnational cocaine trafficking in Europe, and then examining its determinants. The article concludes by identifying the implications for future research. The appendices include further details on the methodology and data adopted.

Illegal enterprise and social embeddedness theories

Illegal enterprise theory springs from general economic theories of crime (Becker 1968; Nettler 1978) by concentrating on the points of overlap between licit and illicit activities. According to this theory, criminals are rational actors engaged in profit-oriented behavior. They are involved in activities that, albeit illegal, are driven by the same laws of supply and demand that determine the legal market (Liddick 1999). This is because there is both a continuum of legal and illegal markets, and a demand for certain goods and services that exists beyond the boundaries of legality (Liddick 1999; Smith 1975). Since the 1970s, there has been broad consensus on illegal enterprise theory; indeed, it has acquired a dominant position in academic debates within most criminological schools (Paoli and Vander Beken 2014). Consequently, many scholars have used interpretation schemes and methods derived from analyses of the legal economy to explain different organized criminal activities, including, *inter alia*, counterfeiting, cigarette trafficking, corruption, fraud (Hetzer 2002; Levi 2008; Passas 1999; Prieger and Kulick 2018; Schelling 1967), as well as drug trafficking (Angrist and Kugler 2008; Castillo et al. 2018; Reuter and Kleiman 1986).

In contradistinction to illegal enterprise theory, social embeddedness theory underscores the differences between legal and illegal activities in terms of cooperation schemes and the behavior of the actors involved (Kleemans 2013). The underlying rationale of this approach is that illegality increases risk and uncertainty, while simultaneously impeding criminals from managing their activities in the same manner that they would if they were operating within a legal environment. This is for three reasons: (i) drug traffickers cannot rely upon legal institutions to settle their disputes or enforce their agreements (Caulkins and Reuter 1998; Jacques and Wright 2011; Paoli 2002; Robles et al. 2013); (ii) drug dealers cannot advertise their products and services or put branding operations in place (Che and Benson 2014; Gambetta 2009); (iii) criminals cannot liquidate their businesses when they wish to exit the market (Collins 1990; Reuter et al. 1990). These and other factors can cause reciprocal distrust and the recourse to violence to become recurring problems in illicit business (Costa Storti and De Grauwe 2008; Gambetta 2000; Kleiman 1989; von Lampe and Ole Johansen 2004). Social embeddedness theory stresses that social relations and the social environment itself play an important role in curbing these problems affecting criminal organizations (Kleemans 2014, 2013; van de Bunt et al. 2014). Speaking the same language, coming from the same socio-cultural background or inhabiting the same institutional setting increase the levels of trust among partners and reduce transaction costs, impacting on how offenders associate with each other (Combes et al. 2005; Kleemans and van De Bunt 1999; Paoli and Reuter 2008).

Transnational cocaine trafficking is a complex criminal activity, whose mechanisms cannot be wholly explained through recourse to a single theoretical perspective; rather, there is a need for "systematic attempts to combine various notions and insights we already have" (Paoli 2014, 5182). Our suggestion is that this mode of theoretical pluralism should comprise both illegal enterprise and social embeddedness theories. Ultimately, a host of factors, some of which are conceptualized by illegal enterprise theory and others by social embeddedness theory, impact on the structure of transnational cocaine trafficking. Indeed, as proposed by illegal enterprise theory, illicit drugs are central to lucrative, clandestine, and transnational markets that obey basic supply and demand rules, whilst economic incentives are the primary drivers of the involvement of groups and individuals in drug trafficking (Albanese 2008; Desroches 2007; Kenney 2007). On the other hand, drug trafficking is embedded in a series of networks of interpersonal relations, but reciprocal distrust is nevertheless a recurring problem (Granovetter 1985; Kleiman 1989). Whence derives the rationale for utilizing social embeddedness theory as well.

Analytical strategy

Researchers have hitherto adopted two main strategies for the empirical investigation of organized crime. At one extreme of the spectrum are those scholars who focus on illicit activities characterized by local dynamics. Reuter (1983) analyzed organized criminal activities such as drug dealing, sexual exploitation, loan sharking, or management of illicit gambling, which are ordinarily defined by local dynamics (Kleemans 2014). Alternatively, other authors have utilized information deriving from police and other criminal justice sources to explore the ties that bind criminals and facilitate their cooperation. This second group of scholars have investigated mafia-type organizations (e.g., Agreste et al. 2016a; Calderoni 2012; Campana 2011) and other less cohesive criminal groups operating in a variety of illicit markets (e.g. Morselli 2009; Malm and Bichler 2011; Bright and Delaney 2013). For instance, Agreste and her co-authors (2016) investigated the resilience of mafia groups to police operations; to this end, they analyzed judicial documents to collect information on forms of interactions among mafia members. This strategy, whilst yielding notable insights into the organizational structure of criminal groups, is nevertheless limited in scope, in that it focuses solely on a specific group that is ordinarily operating either primarily or entirely in one country. In this study we mobilize an additional strategy to investigate organized crime empirically; a strategy which enables us to move beyond solely focusing on illegal activities or social relations, both of them at the local level. This approach moves through three phases: 1) selecting an organized criminal activity—i.e., transnational cocaine trafficking; 2) modeling this activity—i.e., providing a mathematical reconstruction of the cocaine trafficking network; 3) statistically investigating its functioning by operationalizing theories of organized crime—i.e., illegal enterprise and social embeddedness.

With respect to phase 1, in the analysis reported here we concentrated on cocaine trafficking because it is an organized criminal activity and a red flag for organized crime. After conducting an extensive content analysis of definitions of organized crime, Hagan (2006, 134) stated that “"Organized Crime" as syndicate crime (Albini 1971) specifically refers to groups that exhibit a number of the characteristics identified in our content analyses, namely, violence, illicit services and corruption”. The cocaine market has proven to be one of the most violent illicit markets, if, in fact, not the most violent (Moore and Stuart 2005; Reuter 2009; Williams and Felbab-Brown 2012). Whilst illegal drug markets are, in actuality, relatively peaceable (Bacon 2016; Reuter 2009), on occasion, specific drug markets do indeed exhibit high levels of violence, which, in turn, makes them the most violent sector within the illicit economy. The prevalence of corruption is the second indicator of the organized criminal nature of the transnational trafficking of cocaine. Indeed, corruption is one of the most pernicious effects of cocaine trafficking within affected regions (Diaz-Cayeros et al. 2011; UNODC 2011). The necessity of guarding themselves against attacks by law enforcement agencies and rival criminal groups forces drug traffickers to rely on the corruption of public officers and police agents (Dell 2015; Freeman 2006). Third, drug trafficking—including cocaine trafficking—represents one of the principal, and most profitable, illicit activities of many criminal organizations (Reichel 2005).

In addition to this, Hagan (2006, 134) delineates “organized crime” as consisting of those “activities, crimes that often require a degree of organization on the part of those committing them”. From this perspective, cocaine trafficking emerges as a plausible manifestation of organized crime. Indeed, given that cocaine shipments must cross several borders before reaching their final markets (Caulkins 2017), cocaine trafficking requires a certain level of organizational ability (Bruinsma and Bernasco 2004), which has been noted by several authors, including Albini (1971), Beirne and Messerschmidt (2000), Conklin (2009), Maguire and Radoch (1999) and Siegel (2004).

Concerning phase 2, we modelled cocaine trafficking by identifying all known paths used to smuggle cocaine from producing countries to consumer markets in Europe. To reconstruct this macro network of countries, we built on previous work that has applied social network analysis to the geographic configuration of transnational drug trafficking (Berlusconi et al. 2017; Boivin 2013, 2014a; Chandra et al. 2011; Chandra and Joba 2015; Giommoni et al. 2017) (see Appendix A for details on the network construction). Doing so made it possible to estimate the intensity of organized criminal activities in terms of the existence of cocaine flows between any given pair of countries. The strength of the macro(country)-level network analysis stems from its potential to develop general and systematic models of criminal activities—in this case cocaine trafficking—which consider contextual factors which have been shown to be crucial. This would not be possible by analyzing only the behavior of individuals. For instance, the location of countries within a continent—a macro-level feature of a country—helps to explain the specificities of drug trafficking in a specific country (Boivin 2014a).

In phase 3, we operationalized a series of factors related to both illegal enterprise and social embeddedness theories—e.g., price mark-ups, language commonality—to analyze cocaine trafficking statistically (see Appendix B for details on the selection of the independent variables). Doing so enabled us to test theories of organized crime empirically. As said, our hypothesis was that a variety of factors, some of which can be related to illegal enterprise theory and others to social embeddedness theory, impact on the structure of transnational trafficking of cocaine. We used exponential random graph models (ERGMs) to identify the factors that contribute to the probability that a country will trade cocaine with another country in the trafficking network. Our dependent variable was therefore the cocaine trafficking network, and our independent variables included both specific features of either exporting or importing countries (e.g., cocaine users, corruption level) and characteristics of the relations between any two given countries (e.g., geographic distance, migration flows). Appendix C provides information on the model estimation, and Appendix D discusses how we handled missing data.

Results and discussion

The final network comprised 36 European countries that either import cocaine from and/or export cocaine to each other; these countries are connected by 100 trafficking links, i.e. 8% of all possible links (see Table 1). The network's density is lower than would be expected from its size, and indicates that cocaine trafficking is concentrated along a limited number of routes in Europe.[1] This finding of a network characterized by low density matches those of previous criminological studies showing that security is often preferred over efficiency in criminal networks (Morselli et al. 2007). The observed density—i.e., 8% of all possible links—is in line with the low density scores found by previous studies on global cocaine trafficking (Boivin 2014a), and on trafficking in Western Europe alone (Chandra and Joba 2015). Scholars have observed a similar pattern with respect to heroin trafficking at the global level (Boivin 2014a), with respect to the whole of Europe (Giommoni et al. 2017), and in Western Europe (Chandra and Joba 2015).

Analysis of the most frequent triadic configurations and countries' respective positions within them yields understanding of the tradeoff between security and resilience in cocaine trafficking. Of particular note is that, despite the low density of the network, one of the most frequent triadic configurations found was a transitive one whereby two countries, i and j, are both directly linked and connected through an intermediary, k. France, Switzerland, and the Netherlands—located in the heart of Europe—are often in the position of k, i.e. they act as transits between two countries which also share a direct tie. The abundance of triadic configurations partially contradicts previous studies which observed that one efficient drug trafficking route—i.e., a more secure scheme—tends to be preferred over multiple ones—i.e., a more resilient scheme—to provide a market with drugs (Boivin 2014a). Indeed, the presence of transitive ties indicates network redundancy, which in criminal environments may

[1] A conditional uniform graph test (or CUG test) was used to compare the density of the cocaine trafficking network against the density of a baseline model (Butts 2008). A low p-value ($p < 0.001$) suggests that the observed network is less centralized than would be anticipated from its size.

facilitate resilience (Williams 2001). For instance, if customs interrupt trafficking routes to a given country, then traffickers in that country will still be able to procure cocaine via alternative channels. At the same time, the importance of transitive ties suggests that multiple organizations operate in the same country, with each relying on its respective transnational suppliers. For example, Austria receives cocaine from Spain via multiple channels, including Italy and Switzerland.

Table1. Network statistics.

Measures	Statistics
No. countries	36
No. links	100
Network density	0.08
Mean indegree	2.78
Indegree centralization	0.18
Outdegree centralization	0.56

Table 1 also reports the average number of incoming links of the countries in the trafficking network—i.e., the value of the mean indegree. On average, countries import from fewer than three other European countries. However, the number of incoming ties is not equally distributed, with some countries importing cocaine from nine (e.g., Austria) or six other European countries (e.g., Greece and Sweden), respectively. Similarly, most countries export to only one or a few other European countries, while a small number of exporters—i.e. Spain, Germany, and France—have outgoing links to a plethora of other countries (see Appendix E for the full list of countries' centrality scores). Even though previous studies have not identified Spain and France as key countries in the cocaine network (i.e., Chandra and Joba 2015), the centrality of these countries in the European trafficking network is not surprising. Spain is an important and well-known transit point for cocaine coming directly from South America or passing through Africa, while France occupies a central position in Europe both geographically and in terms of international trade (see, for example, Yang et al. 2015), which helps to explain why the two countries are central to illicit traffic. Finally, flow betweenness and betweenness centrality enable identification of those countries that operate as a hub in the trafficking network and, thus, facilitate cocaine flows, namely, Germany, the Netherlands, and Spain. Indeed, Germany and the Netherlands stand out as key hubs also with respect to the trafficking of heroin (Giommoni et al. 2017), suggesting that the explanatory factors behind their role in international trafficking are only partially dependent on the trafficked good, which to some extent contradicts previous analyses that showed the overlaps between the two networks to be marginal (Chandra and Joba 2015).

Table 2 reports the estimates and standard errors from ERGMs of the cocaine trafficking network. Models 1-3 all include both network structural effects and explanatory variables (described in Appendix C and Appendix B, respectively), although the latter differ across the three models. Model 1 includes common language as the only social embeddedness variable. Model 2 adds two variables for geographic proximity—shared borders and distance— whilst Model 3 includes all previous variables and the migration stock between any two given countries.

According to the assumptions of illegal enterprise theory, both trade price mark-ups between any pair of countries and the number of users in importing countries are positively and significantly associated with the probability of forming a tie, thus suggesting that cocaine tends to flow into those countries with large consumer markets where traffickers can make higher profits. Countries with a large number of users, such as the United Kingdom and Italy, import cocaine from several other countries. The tendency to form connections between countries with a higher trade price mark-up further highlights the profit-maximization scheme adopted by traffickers. Hence, they do not simply target those countries providing more business opportunities (i.e., large markets), but also those that guarantee higher profits per unit. In this respect, drug trafficking flows resemble the supply of legal products and appear to be driven by economic forces, in particular business opportunities and profits (Gundur 2019; South and Wyatt 2011). As reported by other sources, drug use prevalence tends to be higher in more developed regions than in poorer and developing countries (Babor et al. 2010). In addition to price dynamics, it must also be considered that more affluent countries tend to be more effective in controlling their territory; as a consequence, local criminal groups have difficulties in producing drugs locally (Boivin 2014a).

Besides maximizing their own revenues, organized criminals also attempt to reduce their risks, as envisaged by illegal enterprise theory. Corruption and police rates in the importer country are adopted as operationalization of risks for traffickers. In all three models, corruption in importing countries plays a crucial role in tie formation.[2] Corruption reduces the risks for criminals trafficking cocaine, in that it provides them with protection against arrests and seizures (Basu 2014). Nonetheless, we cannot exclude a reciprocal influence of corruption on cocaine trafficking. Indeed, it is entirely possible that the relation goes in the other direction, and that it is actually organized criminals trafficking cocaine that fuel corruption (Chalk 2011; Moore and Kleiman 1989). However, the inclusion of a generic indicator of corruption, rather than one specifically related to drugs, appears to indicate that corruption plays a role in creating trafficking flows, not vice versa. As with previous studies investigating heroin trafficking (Giommoni et al. 2017), the strength of law enforcement actions, measured by countries' number of police officers per inhabitant, appears to be ineffective in discouraging the formation of cocaine trafficking routes; in fact, the estimates for the variable are consistently non-significant across all models. This result is supported by several other empirical studies that demonstrate that law enforcement strategies are unable to eliminate the supply of illegal drugs (MacCoun and Reuter 2001; Pollack and Reuter 2014).

Social embeddedness theory was tested using measures of social—and geographical—proximity between countries. Countries in which part of the population speaks the same language have a higher probability of cocaine flows between them than countries that do not (Model 1). This correlation suggests that speaking the same

[2] Estimates of the effects of corruption are not statistically significant when alternative imputation methods for missing nodal attribute data are used. Appendix D provides details on missing data and alternative imputation methods. Appendix G reports the results of the robustness checks, where we used alternative methods to impute missing values. Results remain similar in both direction and magnitude in all the models; levels of significance are also similar, albeit with one exception. The estimates for the levels of corruption in importing countries lose statistical significance in the models based on networks where missing nodal attribute data were imputed using predictive mean matching and bootstrapping, and mean substitution.

language plays a role in reducing the transaction costs in a hostile environment in which drug traffickers operate. However, when we control for countries' shared borders, the correlation between commonality of language and the presence of trafficking links ceases to be statistically significant (Model 2). In Europe, it is not rare that neighboring countries comprise communities that speak the same language—e.g., French-speaking communities in France, Luxembourg, Belgium, the Netherlands, and Switzerland; Serbian-speaking communities in Serbia, Bosnia and Herzegovina, Kosovo, Croatia, and Montenegro—so that the socio-linguistic effect and the geographic one are difficult to isolate. Model 3 also shows that paired countries with intense migration flows are more likely to traffic cocaine with each other, thus lending support to the findings of previous studies on the influence of migration patterns on drug trafficking routes (Akyeampong 2005; Giommoni et al. 2017; Paoli and Reuter 2008; Zaitch 2002). The positive correlation between ethnic ties and illicit trafficking underlines the importance of social embeddedness for criminal groups engaged in transnational trafficking. This finding contradicts the results of recent studies on drug supply (e.g., McLean et al. 2019). Sharing the same ethnic background reduces uncertainties in a context dominated by the constant threat of arrest, violence and deception. Because traffickers cannot resort to legal authorities to enforce their agreements, they must be especially careful when choosing their trading partners. Traffickers from the same ethnic background can thus rely on non-economic factors to better their trading agreements (Kleemans and van De Bunt 1999; Paoli and Reuter 2008).

Geographic distance between countries is not significantly associated with cocaine flows when migration flows are taken into account. This is reasonable considering that the framework of our research is Europe. On the one hand, distances are relatively small, while the guarding of EU internal borders is relatively lax once the cocaine has reached the main gatekeeper transit points between South America and Europe. In consideration of this factor, (short) land routes may be a valuable option for moving drugs within Europe. On the other hand, maritime ports are key entry points for cocaine flowing from South America; from ports, cocaine can be further transferred via (long) sea connections (EMCDDA and EUROPOL 2016). Our models suggest that cocaine shipments are not necessarily concentrated into short connections.

The results also show the importance of the EU's external borders. Countries belonging to the Schengen area are more likely to be connected by trafficking routes. Border controls among countries belonging to the Schengen area are, in fact, minimal and purposely designed to facilitate trade among member states. Conversely, the connection between non-Schengen and Schengen countries is not significant, thus highlighting the greater efforts required of traffickers in crossing the EU's external border and gaining access to the European market. The EU's border does not appear to have the same importance in terms of controlling cocaine flows in the other direction. The connection from Schengen to non-Schengen countries is in fact significant and positive in Models 2 and 3. This may indicate that the same European countries serve as transit points between South America and non-EU countries (e.g., Eastern European countries). Finally, European countries importing cocaine from non-European countries are more likely to have connections with many others. This means that these countries (e.g., the Netherlands and Spain) are the key entry points and re-distribution centers for cocaine exported from South America to Europe.

Among the network structural effects included in the models, the importer effect is the only one statistically significant across all of them. A positive coefficient estimate suggests that the network is centralized on indegree, i.e. that a few countries act as trafficking hubs in the network, whilst most of them are only marginally involved in cocaine trafficking. This confirms the analysis of indegree centrality scores, which helped identify several countries that do not have any outgoing ties and import cocaine for internal consumption only. It also confirms previous findings on the structure of global and European drug trafficking networks, which are usually characterized by varying levels of activity among the countries involved (Boivin 2014a; Chandra and Joba 2015; Giommoni et al. 2017). In Model 3, the estimate for simple connectivity is negative and statistically significant, suggesting that countries tend not to be active exporters and importers simultaneously; rather, different countries tend to be either active exporters or active importers of cocaine.

Table 2. Estimates and standard errors from ERGMs of the cocaine trafficking network.

	Model 1			Model 2			Model 3		
Parameter	Estimate		SE	Estimate		SE	Estimate		SE
Structural effects									
Edges	-33.344	***	0.125	-29.926	***	0.120	-33.270	***	0.127
Reciprocity	0.388		0.839	-0.014		0.881	-0.033		0.853
Exporter effect	1.083		0.792	1.264		0.813	0.978		0.800
Importer effect	3.387	**	1.283	3.584	**	1.378	3.970	**	1.332
Simple connectivity	-0.163		0.112	-0.202		0.110	-0.249	*	0.109
Multiple connectivity	-0.171		0.135	-0.131		0.134	-0.098		0.129
Transitivity	-0.097		0.251	-0.163		0.255	-0.219		0.251
Illicit enterprise variables									
Trade price difference	0.786	**	0.243	0.663	*	0.263	0.577	*	0.272
Importer – cocaine users	0.524	***	0.110	0.569	***	0.119	0.514	***	0.117
Importer – police rate	-0.001		0.001	-0.001		0.001	-0.001		0.001
Importer – corruption	0.318	**	0.118	0.330	*	0.136	0.311	*	0.129
Social embeddedness variables									
Common language	1.270	*	0.552	0.284		0.641	0.169		0.649
Migration stock (ln)							0.243	**	0.080
Distance (ln)				-0.472		0.294	-0.158		0.309
Shared borders				1.114	*	0.485	0.869		0.489
Controls									
Importer – GDP per capita (ln)	0.865	**	0.327	0.880	*	0.353	1.088	**	0.339
Schengen to non-Schengen	1.899		1.047	2.156	*	1.060	2.203	*	1.069
Non-Schengen to Schengen	1.471		1.131	1.745		1.147	2.012		1.171
Schengen to Schengen	3.328	**	1.122	3.527	**	1.140	3.836	***	1.161
Exporter – cocaine imported from non-European countries (ln)	0.900	***	0.124	0.977	***	0.139	0.790	***	0.139

Note. SE = standard error. * p < .05; ** p < .01; *** p < .001.

Conclusions

This study has tested illegal enterprise and social embeddedness theories in relation to a specific organized crime activity, i.e. transnational cocaine trafficking. Specifically, it has adopted a macro-network analysis approach to explain why cocaine traffickers choose some trafficking routes instead of others. It was found that both theories to some extent explain the formation of cocaine trafficking flows in Europe. As postulated by illegal enterprise theory, the maximization of economic returns and the reduction of risk drive cocaine trafficking in some specific countries, avoiding others. Cocaine tends to flow to richer countries where the demand for the drug is high and users can afford to spend more money on it. These countries provide traffickers with greater business opportunities and with potentially higher economic returns. Traffickers are, however, also responsive to negative economic incentives. Countries characterized by high levels of corruption are likely to become part of important trafficking routes, whereas countries with strong institutions and low levels of corruption can impose higher non-monetary costs on traffickers. While bribing officials is an initial cost, it nevertheless reduces the risk of arrest and interception for traffickers. Traffickers are thus more than willing to sacrifice part of their immediate economic returns to ease the traffic of drugs across borders and, in turn, guarantee their impunity. In this regard, cocaine trafficking has remarkable similarities with many legal forms of trade. Indeed, in many respects, criminal groups appear to behave like all other suppliers of a commodity which is not locally available in many markets: they act as rational and profit-driven businesses, and aim to achieve higher returns at lower costs. Although the product that they market is illegal, the formation of cocaine trafficking routes is nonetheless driven by the normal laws of supply and demand. However, illegal enterprise theory can only account for part of the phenomenon.

To understand cocaine trafficking fully, we must look at the social connections 1) between countries trading cocaine with each other, 2) between communities living in them, and consequently 3) between criminal groups active in them. As Kleemans (2014, 37) puts it: "[o]rganized crime does not operate within a social vacuum, but interacts with its social environment". Organized crime activities that are intrinsically financially-driven are thus embedded in informal networks. While criminals are in the business of making money, what brings them together, in most cases, is friendship, family ties, or the same background, ethnicity, language and cultural values (Lipsey and Derzon 1998; Pratt and Cullen 2005).

There are two reasons why organized crime activities are embedded in social ties. First, given the illegality of cocaine, traffickers need to rely on informal factors to find—and trust—their trading partners. As they cannot recruit business partners via legal instruments (e.g., job advertisements), strong ties, such as family connections or friendship, as well as weak ties (from acquaintanceship to sharing the same ethnicity and speaking the same language) provide easier access to valuable information and present opportunities for business. As in any other network, the smaller the social and geographical distance between two people, the greater the likelihood that they will cooperate (Malm et al. 2010). This explains, in part, the role of Turkish, Albanians and Nigerian groups in the international trafficking of cocaine and heroin in Europe (Paoli and Reuter 2008). All these ethnic groups have engaged in large-scale migration to several countries, and rely on sociocultural factors (e.g., reputation and trust in suppliers, ethnic ties) as means through which to find international partners. Second, social relations help reduce the uncertainties inherent to a hostile market. Traffickers cannot resort to legal authorities to ensure compliance with their business agreements; nor can they turn to insurance companies, mediators or banks to help resolve disputes and disagreements (Paoli 2002). In this context, sharing the same cultural background, language and cultural heritage reduces uncertainties and increases reciprocal trust.

This study is one of the first attempts to merge two of the most debated theories in the study of organized crime. It shows that illicit enterprise and social embeddedness theories can be used jointly to explain different features of the same phenomenon. While illicit enterprise theory highlights the rationality and business-oriented nature of cocaine traffickers, social embeddedness theory stresses the social background of cocaine trafficking flows. The two theories are thus complementary rather than mutually exclusive. Criminal groups try to increase their profits and reduce their risk, while simultaneously relying on migration connections when deciding where to traffic cocaine. Consequently, the arguments proposed by the two theories are not contradictory, but instead complementary.

In this study we have applied a new approach to test theories of organized crime empirically. We have shown that, despite the shortage of direct empirical data on organized crime, it is still possible to develop creative approaches to proxy for organized crime behaviors. Micro-level dynamics—those concerning organized criminal groups—can be modeled by exploiting information at the macro-level—national-level statistics— which are usually easier to obtain. While this methodology has been tested with a specific focus on European countries, there is no reason why it could not be adopted to study other geo-political contexts. On this basis, future research could seek to advance the theoretical study of organized crime in two ways. First, illegal enterprise and social embeddedness theories could be exploited further to investigate other traditional organized crime activities, such as human or wildlife trafficking, as well as the trafficking of other illicit drugs. Second, even though illicit enterprise and social embeddedness theories are among those most widely adopted to explain organized crime, several other theoretical perspectives have made expedient contributions to the explanation of organized crime (for instance, routine activity or situational crime prevention). The inclusion of these theoretical frameworks could help to shed further light on the structure and functioning of organized crime.

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Appendices

Appendix A. Dependent variable

Cocaine trafficking between European countries is the dependent variable in our empirical analysis. Connections, and more generally the structure of transnational cocaine trafficking, are assumed to reflect the strategies adopted by cocaine traffickers. The necessity of a geographical boundary (i.e., Europe) stems from the fact that we do not want to investigate types of traffic which are intrinsically different—i.e., interregional and intraregional. Interregional shipments target countries which are mainly transit points (e.g., from South America to Western Africa), while intraregional traffic (e.g., from Spain to other EU Member States) is likely to be driven by slightly different strategies. For instance, with respect to interregional traffic, the demand for cocaine in a local market is expected to have a minor influence on the selection of a given route. At the same time, our focus on intraregional traffic between European countries is also expedient because European countries produce a larger amount of data compared to other regions.

In accordance with previous studies (Boivin 2011; UNODC 2015b; Giommoni et al. 2017), we have identified the existence of cocaine flows both from and to European countries. We have done so by drawing upon information on seizure cases that occurred between 2009 and 2012; information which was collected from the UNODC individual drug seizure (IDS) dataset. The IDS dataset comprises 65,426 records on seizures of coca and derivatives that occurred during the period considered. The available information states the weight of the intercepted drug loads, the country performing the seizures, and, in the case of 15,524 of these seizure cases, a combination of information about the origin, destination, and last transit country. This information enables the identification of 794 different pairs of countries exchanging cocaine during the period 2009-2012. 365 of the identified dyads accounted for less than 1% of the seizures in the importing country and, consequently, were removed from the network. This procedure made it possible to concentrate on more relevant and definitive connections, while simultaneously eliminating occasional cocaine flows (Giommoni et al. 2017). As said above, a geographic criterion was used to set a second boundary for the final network, which only included connections involving two European countries.[3] The resulting network comprised 36 European countries, while the total number of dyads was 100 (see Appendix E for the full list of countries).

The network construction suffers from two main limitations. First, some countries do not report information to the UNODC annually, while others avoid sharing any information at all about seizures. This issue is alleviated to some extent by the fact that the role of a country can also be inferred by examining information provided by other countries, as well as by using average data that cover a four-year period (Berlusconi et al. 2017). Nonetheless, the final network is still likely to underestimate the complexity of actual cocaine trafficking. Second,

[3] Countries are labelled as European or not according to the division of macro geographic regions used by the United Nations (UNODC, 2015a).

it is reasonable to expect a certain degree of heterogeneity in countries' responses to drug trafficking; moreover, within any given country, air and sea routes tend to be policed more rigorously in comparison to land routes. Therefore, information on seizures may cause an over-estimation of the amount of cocaine trafficking in more aggressive countries and pertaining to sea and air routes (Reuter 2014). Given the focus on the existence of trafficking connections as opposed to their size, enforcement-related biases are expected to affect only the definition of the network boundary based on the amount of the flows.

Appendix B. Independent variables

The selection of the independent variables was based on the illegal enterprise and social embeddedness theories, which led to the inclusion of both nodal and relational attributes data (Table B1). The former refers to specific features of either exporting or importing countries, while the latter refer to characteristics of the relations between any two given countries.

Table B1. Source and descriptive statistics of independent variables.

Nodal attribute	Source	Min.	Max.	Mean	St. Dev.
GDP per capita	World Bank, avg. 2009-2012	3,234	153,817	35,711	31,954
Wholesale prices (purity-adjusted), USD/kg	Authors' elaboration on UNODC data, avg. 2009-2012	35,422	304,657	129,074	63,221
Cocaine users	UNODC, 2009-2012	447	827,733	102,783	195,186
Police agents, rate per 100,000 population	UNODC, avg. 2009-2012	87.9	1,503.6	373.5	224.5
Corruption perceptions index	Transparency International, avg. 2009-2012	24	92	60	21
Imports from non-European countries, kg	Authors' elaboration on UNODC data, 2009-2012	0	114,987	7,759	20,029
Relational attribute	**Source**	**Network size**	**Edge count**	**Density**	**Mean degree**
Language spoken by at least 9% of the population in both countries	CEPII, 2000-2008	36	46	0.07	1.3
Migrant (stock)	UNGMD, 2010	36	1,127	0.89	62.6
Weighted distance	CEPII	36	1,260	-	-
Border adjacency	CEPII	36	130	0.21	3.6
Schengen area member states	Authors' elaboration	36	325	0.52	18.1

Note. UNODC = United Nations Office on Drugs and Crime; CEPII = Centre d'Etudes Prospectives et d'Informations Internationales; UNGMD = United Nations Global Migration Database.

According to illegal enterprise theory, organized criminals are rational individuals who aim to maximize their profits, whilst, simultaneously, minimizing their risks (Haller 1990)—i.e., seizure and apprehension. We expect traffickers' profits to be associated with the number of cocaine users in importing countries whilst controlling for cocaine users' ability to pay for drugs, which is proxied by countries' GDP per capita. Traffickers may also take into account the differences in wholesale prices in any two countries when selecting the most profitable drug route or destination country, ultimately choosing to direct their shipments to countries where margins are largest. Having said this, price mark-ups can also be influenced by the risks associated with trafficking, as well as by an individual country's position and role within the global cocaine market (Boivin 2014b). With respect to traffickers' risks, in light of the limitations of extant data on drug-related arrests (Kilmer et al. 2015), we followed previous studies by using the rate of police officers per 100,000 population as a proxy for the capacity of law enforcement to arrest traffickers and intercept shipments (Boivin 2014b; Giommoni et al. 2017). Transparency International's Corruption Perceptions Index (CPI) (2019) was included as a means with which to account for drug traffickers' reliance on the corruption of public officers and law enforcement agents to facilitate cocaine trafficking (Dell 2015; Freeman 2006).[4] Despite the widespread use of the national rate of police officers and of synthetic indexes of corruption in other macro-level studies, the capacity of these variables to operationalize the risk for traffickers is partial at best. For instance, larger police forces might not be correlated with stricter enforcement against drug trafficking if priorities, equipment, and training are not standardized across countries. The issue with corruption indexes is twofold. Firstly, corruption is a phenomenon that may be conceptualized in different ways according to different cultural contexts; and secondly, synthetic indexes are generic indicators which do not focus specifically on the corruption schemes that facilitate cocaine trafficking—e.g., among custom officials.

Social embeddedness theory stresses the importance of social relations and the social environment for understanding organized crime activities. Speaking the same language or coming from the same socio-cultural background can help to build trust between illicit business partners and reduce transaction costs (Combes et al. 2005; Kleemans and van De Bunt 1999; Paoli and Reuter 2008). Consequently, our independent variables included the presence of a language spoken by at least 9% of the population in any two given countries, as well as the number of migrants, for each country, in relation to their country of origin. We also considered the role of geographical distance (Mayer and Zignago 2011) and shared borders as factors that might reduce transaction costs and facilitate drug trafficking, particularly in terms of land transport (Reuter 2014). At the same time, geographical closeness partially overlaps with the use of common languages—e.g., Germany-Austria-Switzerland—as well as migration flows—e.g., Germany-Poland.

Finally, given that our European network is part of a larger international trafficking network, we controlled for countries importing cocaine directly from non-European countries. We did so because countries which act as transit points between South America—and Western Africa—and Europe are more likely to have stronger ties with other European countries (e.g., see Boivin 2014a). We also considered countries' membership of the Schengen area, because customs and border controls of goods flowing among Schengen member states are minimized. In consideration of this fact, traffickers might prefer to use these routes over alternative ones.

[4] The index ranges from 0 for highly corrupt countries to 100 for very honest countries. We use the reciprocal of the index so that higher values indicate higher corruption levels.

Appendix C. Model estimation

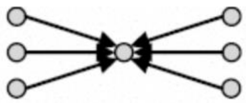
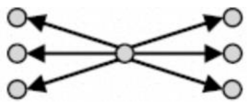
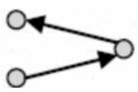
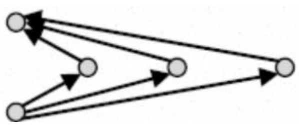
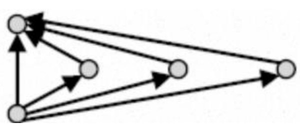
Exponential random graph models (ERGMs) were used to predict the probability of tie formation—i.e., the probability that a country would trade cocaine with another country in the trafficking network. ERGMs are a class of statistical models that account for the presence of network ties based on a set of nodal and relational attribute data, as well as on the properties of the network itself (Robins et al. 2007; Lusher et al. 2013). ERGMs formulate the probability of observing a set of ties as:

$$P(Y = y|X) = \exp\,[\theta^T g(y, X)/k(\theta)]$$

where Y is the set of ties in a network, y is a particular given set of relations, X represents a matrix of attributes for the countries in the network, $g(y, X)$ is a vector of network statistics, θ corresponds to the vector of coefficients, and $k(\theta)$ is a normalizing constant (Goodreau et al. 2008). The analyses were performed using the statnet suite of packages (Handcock et al. 2018) for R (R Core Team 2018). For dyad dependence models, the maximum likelihood was approximated by using Markov Chain Monte Carlo simulation methods (Hunter, Handcock, et al. 2008). Appendix F includes the results of goodness-of-fit checks for the models presented in Table 2 in the Results and Discussion section. The goodness-of-fit checks were performed using the procedure outlined in the work of Hunter, Goodreau, and Handcock (2008).

Compared to other "traditional" statistical models, ERGMs take into account dependencies among observations, and enable the identification of both the effects of covariates (i.e., the nodal and relational attributes discussed in the previous section) and the effects of network parameters (Lusher et al. 2013). The latter are estimated by including parameters for importer and exporter effects, reciprocity, simple and multiple connectivity, and transitivity (Lusher et al. 2013; Thurner et al. 2018). In light of previous research on drug trafficking networks (Giommoni et al. 2017), we expected there to be a small number of countries with several incoming and/or outgoing ties, and a large number of countries which imported from and/or exported to a limited number of other countries. This could be due to the presence of countries which act as regional transits, gatekeepers or regional hubs, which thus have a particularly active role in the trafficking network (Boivin 2014a; Giommoni et al. 2017). Geometrically weighted indegree (gwideg) and outdegree (gwodeg) were used to assess whether countries had similar levels of activity, or whether the network was centralized around a few trafficking hubs (Hunter 2007; Goodreau et al. 2008) (Table C1). If countries in the network were both active importers and exporters of cocaine, then we would expect positive parameters for both simple and multiple connectivity, which were estimated by using 2-paths (twopath) and geometrically weighted dyad-wise shared partners (gwdsp). However, the latter is ordinarily negative when there is a high degree of closure in the network, i.e., when two trading countries share many other trading partners (Lusher et al. 2013; Thurner et al. 2018). Network closure was estimated by using geometrically weighted edgewise shared partners (gwesp), which accounted for the probability of transitive triads in the network (Hunter 2007). The presence of transitive triads was also assessed through an analysis of the network triad census—i.e., the count of different types of triads in a network— which provides insight into structural patterns such as differential popularity, transitivity, or reciprocity of relations (Wasserman and Faust 1994; Holland and Leinhardt 1970). Finally, we sought to capture the probability of reciprocal ties between any two given countries (mutual), which we expected to be negative.

Table C1. Network parameters.

Parameter		statnet name	Interpretation
Edge		edges	Baseline propensity for tie formation.
Reciprocity		mutual	A positive parameter indicates that reciprocated ties are likely to be observed.
Importer effect		gwideg	A positive parameter indicates that the network is centralized on indegree.
Exporter effect		gwodeg	A positive parameter indicates that the network is centralized on outdegree.
Simple connectivity		twopath	A positive parameter indicates that countries that send ties also receive them.
Multiple connectivity		gwdsp	A negative parameter in conjunction with a positive transitivity parameter indicates that 2-paths tend to be closed.
Transitivity		gwesp	A positive parameter indicates that there is a high degree of closure (i.e. two trading countries have many other common trading partners).

Note. Adaptation of Lusher et al. (2013, 175), Wang et al. (2009, 34) and Thurner et al. (2018, 12).

Appendix D. Missing data and robustness checks

The statnet package used to fit ERGMs cannot handle missing attribute data, which confronted us with two main challenges. First, the original data sources did not always provide information for all the 36 European countries included in the cocaine trafficking network. For instance, Transparency International's Corruption Perceptions Index is not available for Monaco. For those countries with missing data, we calculated the region average based on the division into macro geographic regions used by the United Nations (e.g., the Western Europe mean for Monaco) (UNODC 2015a). Second, even when the original data sources included all 36 European countries, some variables may have been lacking data for those years under consideration. The UNODC, for example, does not report the rate of police officers in Belarus after 2004. In this case, the last data point available was used rather than the 2009-2012 average. The CEPII dataset—which was used as a source of information for language shared by at least 9% of the population in two given countries, and the geographic distance and shared borders between any two countries—represented an additional challenge because it either does not include some countries (e.g., Monaco) or includes an old classification (i.e., Serbia and Montenegro as a single country). French data on language and geographic distance were assigned to Monaco to overcome this missing data problem. Data for Serbia and Montenegro were assigned to both Serbia and Montenegro, which were treated as two separate countries in our network. Missing data on shared borders were imputed manually. Alternative methods for imputing missing values were used to check the robustness of the results. Missing nodal attribute data were imputed using predictive mean matching and bootstrapping (Horton and Kleinman 2007), which were performed through the aregImpute function with the Hmisc package for R (Harrell 2019). The same package was also used to treat missing values using mean substitution. The results of the ERGMs based on networks where missing nodal attributed data were imputed using these methods are reported in Appendix G.

Appendix E. List of countries and their centrality scores

Table E1. List of countries and their centrality scores.

Code	Country	Indegree centrality	Outdegree centrality	Betweenness	Flow betweenness
AUT	Austria	9	0	0.00	0.00
BEL	Belgium	3	2	4.87	4.18
BGR	Bulgaria	3	1	3.00	5.62
BLR	Belarus	1	0	0.00	0.00
CHE	Switzerland	5	3	5.53	8.99
CZE	Czech Republic	4	1	0.00	0.95
DEU	Germany	2	20	71.33	85.76
DNK	Denmark	5	1	5.45	6.70
ESP	Spain	1	22	11.02	13.90
EST	Estonia	1	0	0.00	0.00
FIN	Finland	2	0	0.00	0.00
FRA	France	1	20	6.20	9.41
GBR	United Kingdom	4	1	0.45	0.87
GRC	Greece	6	0	0.00	0.00
HRV	Croatia	3	1	1.00	1.42
HUN	Hungary	5	0	0.00	0.00
IRL	Ireland	3	0	0.00	0.00
ISL	Iceland	1	0	0.00	0.00
ITA	Italy	4	3	11.70	12.92
LTU	Lithuania	1	0	0.00	0.00
LUX	Luxembourg	3	0	0.00	0.00
LVA	Latvia	1	1	0.00	1.50
MCO	Monaco	1	0	0.00	0.00
MLT	Malta	2	0	0.00	0.00
MNE	Montenegro	1	0	0.00	0.00
NLD	The Netherlands	5	4	35.32	41.77
NOR	Norway	2	0	0.00	0.00
POL	Poland	4	1	7.00	7.00
PRT	Portugal	1	14	1.83	4.08
ROU	Romania	1	2	0.00	0.51
RUS	Russia	2	0	0.00	0.00
SRB	Serbia	2	1	0.00	1.50
SVK	Slovakia	1	0	0.00	0.00
SVN	Slovenia	3	0	0.00	0.00

SWE	Sweden	6	2	12.30	13.84
UKR	Ukraine	1	0	0.00	0.00

Appendix F. Goodness-of-fit plots

Figure F1. Goodness-of-fit plots for Model 1.

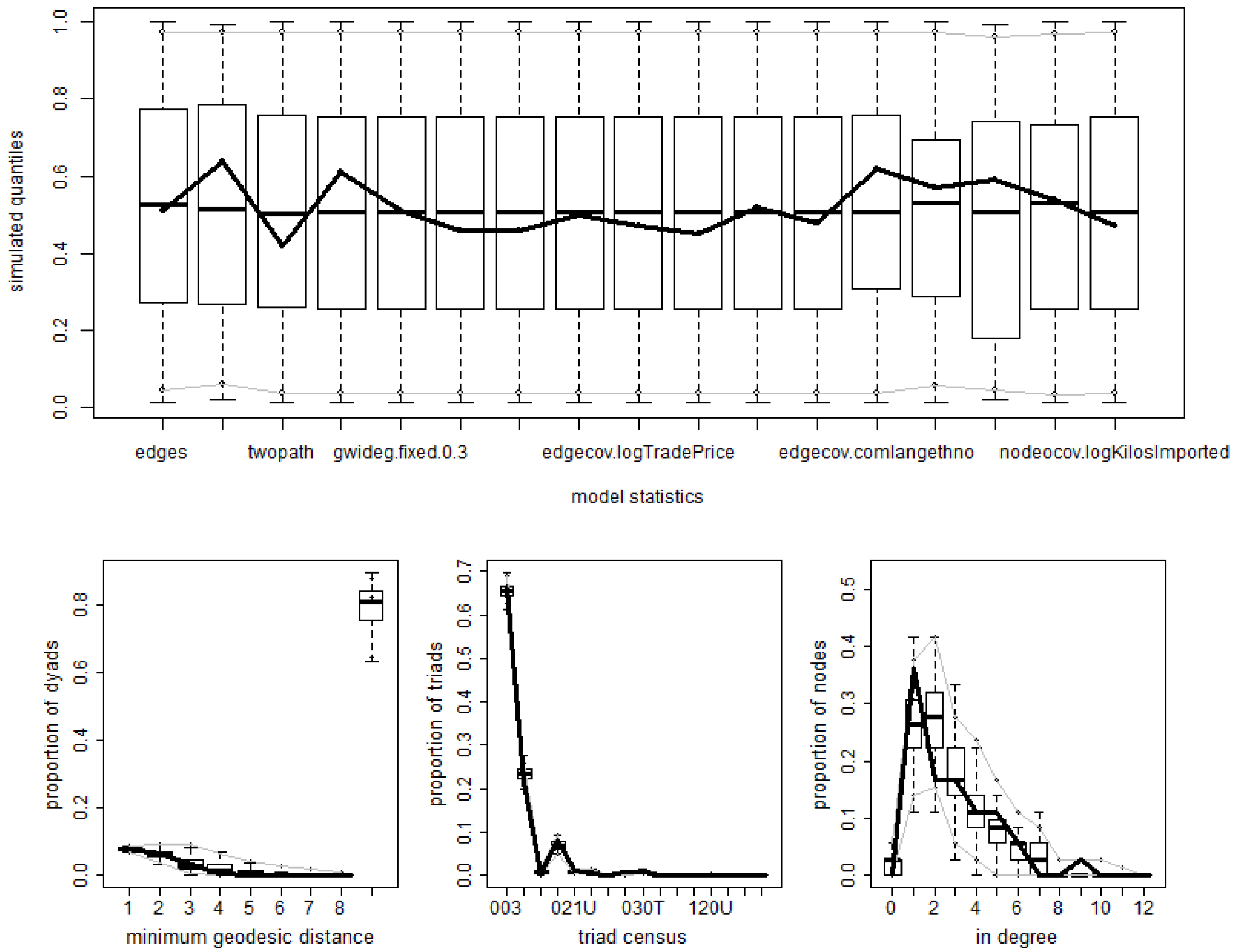


Figure F2. Goodness-of-fit plots for Model 2.

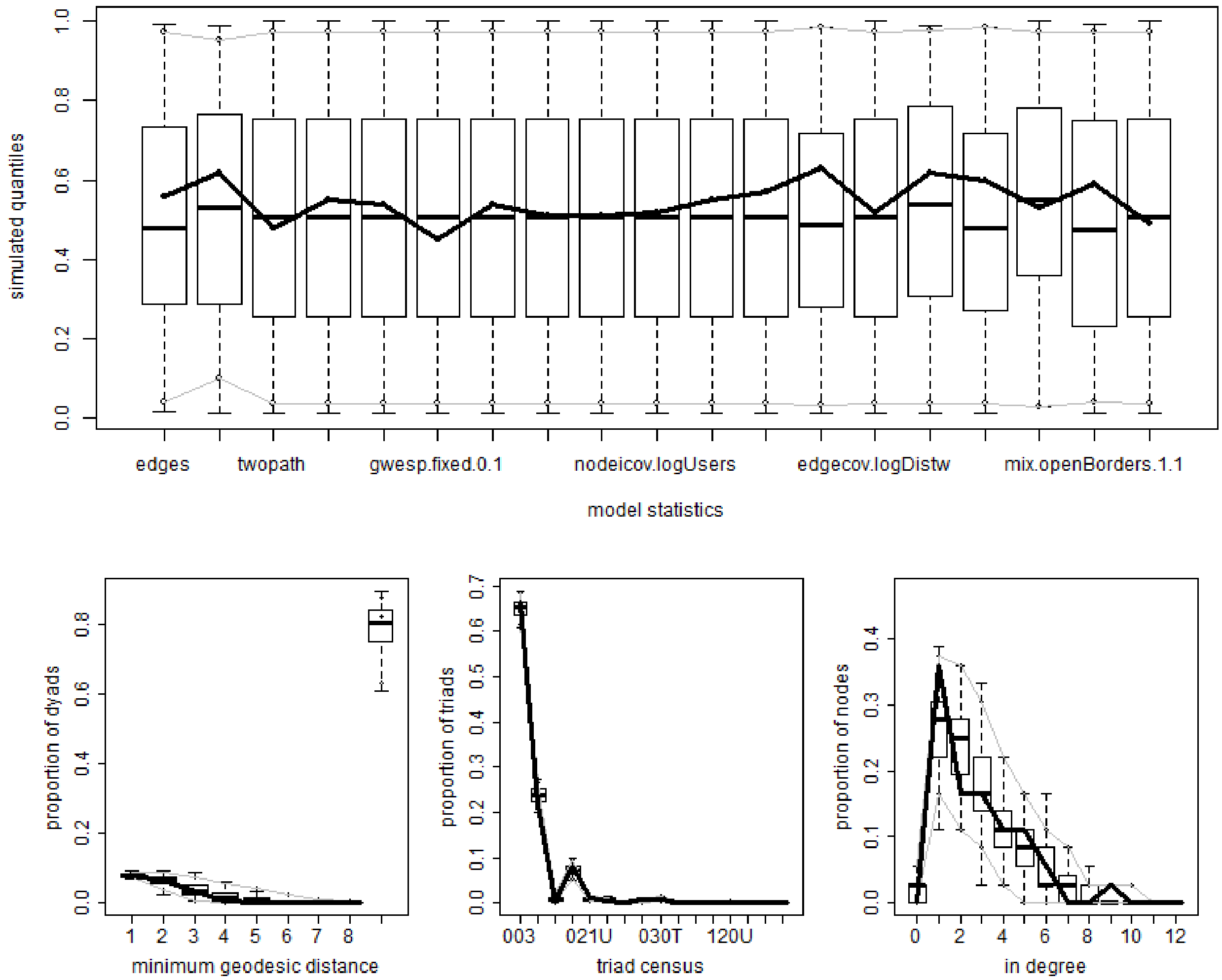
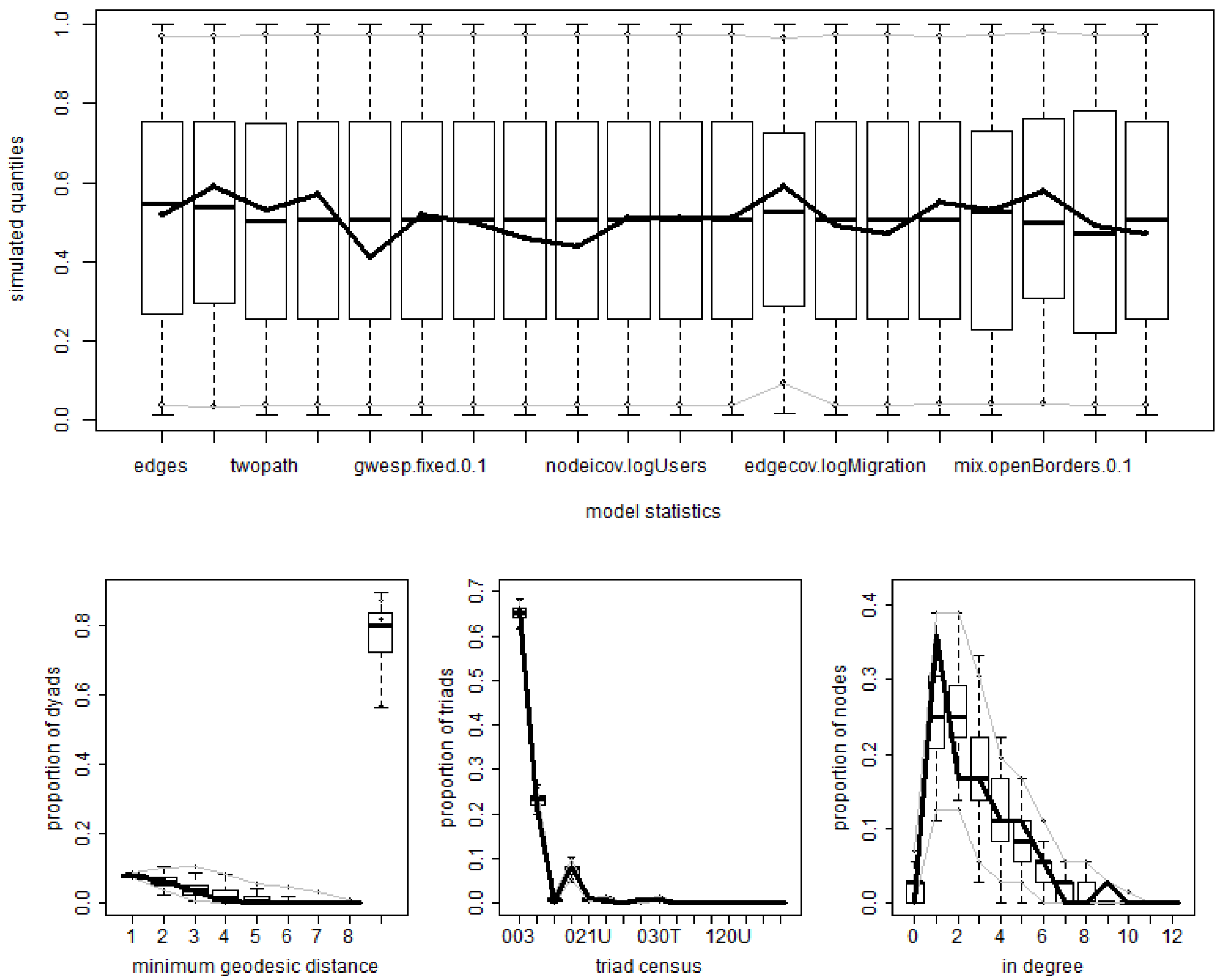


Figure F3. Goodness-of-fit plots for Model 3.



Appendix G. Additional ERGM estimates and standard errors

Table G1. Estimates and standard errors from ERGMs of the cocaine trafficking network where missing nodal attribute data are imputed using predictive mean matching and bootstrapping.

	Model 4			Model 5			Model 6		
Parameter	Estimate		SE	Estimate		SE	Estimate		SE
Structural effects									
Edges	-33.326	***	0.117	-29.848	***	0.120	-33.096	***	0.113
Reciprocity	0.335		0.842	-0.047		0.866	-0.075		0.844
Exporter effect	0.987		0.784	1.199		0.800	0.903		0.791
Importer effect	3.109	*	1.283	3.212	*	1.267	3.504	**	1.256
Simple connectivity	-0.171		0.111	-0.207		0.109	-0.253	*	0.108
Multiple connectivity	-0.168		0.134	-0.131		0.133	-0.090		0.128
Transitivity	-0.123		0.252	-0.180		0.255	-0.236		0.252
Illicit enterprise variables									
Trade price difference	0.839	***	0.233	0.717	**	0.254	0.617	*	0.272
Importer – cocaine users	0.557	***	0.099	0.601	***	0.108	0.528	***	0.113
Importer – police rate	0.002		0.002	0.002		0.002	0.002		0.002
Importer – corruption	0.132		0.131	0.150		0.143	0.132		0.144
Social embeddedness variables									
Common language	1.233	*	0.555	0.250		0.645	0.126		0.652
Migration stock (ln)							0.244	**	0.079
Distance (ln)				-0.470		0.295	-0.155		0.308
Shared borders				1.119	*	0.484	0.873		0.493
Controls									
Importer – GDP per capita (ln)	0.553		0.294	0.566		0.316	-0.090		0.128
Schengen to non-Schengen	1.940		1.015	2.193	*	1.055	2.249	*	1.039
Non-Schengen to Schengen	1.645		1.104	1.913		1.138	2.119		1.141
Schengen to Schengen	3.547	**	1.093	3.742	***	1.128	3.996	***	1.129
Exporter – cocaine imported from non-European countries (ln)	0.891	***	0.121	0.968	***	0.136	0.784	***	0.135

Note. SE = standard error. * p < .05; ** p < .01; *** p < .001.

Table G2. Estimates and standard errors from ERGMs of the cocaine trafficking network where missing nodal attribute data are imputed using mean substitution.

	Model 7			Model 8			Model 9		
Parameter	Estimate		SE	Estimate		SE	Estimate		SE
Structural effects									
Edges	-31.217	***	0.127	-27.905	***	0.123	-31.517	***	0.127
Reciprocity	0.350		0.844	-0.037		0.874	-0.050		0.849
Exporter effect	0.989		0.780	1.183		0.801	0.861		0.791
Importer effect	2.915	*	1.218	3.065	*	1.260	3.330	**	1.239
Simple connectivity	-0.160		0.109	-0.197		0.109	-0.243	*	0.106
Multiple connectivity	-0.175		0.132	-.0137		0.133	-0.096		0.125
Transitivity	-0.115		0.249	-.0175		0.254	-0.233		0.249
Illicit enterprise variables									
Trade price difference	0.786	***	0.230	0.669	**	0.253	0.575	*	0.274
Importer – cocaine users	0.565	***	0.099	0.607	***	0.111	0.533	***	0.115
Importer – police rate	0.002		0.002	0.002		0.002	0.002		0.002
Importer – corruption	0.074		0.130	0.083		0.143	0.074		0.147
Social embeddedness variables									
Common language	1.189	*	0.533	0.206		0.646	0.099		0.656
Migration stock (ln)							0.247	**	0.079
Distance (ln)				-0.448		0.291	-0.129		0.303
Shared borders				1.157	*	0.484	0.900		0.492
Controls									
Importer – GDP per capita (ln)	0.374		0.280	0.380		0.302	0.646	*	0.317
Schengen to non-Schengen	1.890		1.004	2.167	*	1.051	2.223	*	1.063
Non-Schengen to Schengen	1.629		1.094	1.916		1.138	2.122		1.166
Schengen to Schengen	3.503	**	1.080	3.700	***	1.123	3.961	***	1.145
Exporter – cocaine imported from non-European countries (ln)	0.887	***	0.122	0.962	***	0.139	0.776	***	0.138

Note. SE = standard error. * p < .05; ** p < .01; *** p < .001.