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Three Essays on Social Mechanisms in Financial Markets

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Abstract

A major line of network research depicts financial markets as sets of interdependent trading relations connecting buyers and sellers of financial resources over time. Even if the view of financial markets, and indeed of markets in general, as complex relational systems is not new, what has been missing so far is a principled analytical framework to connect this view to the relational structure of financial markets that emerges from observed trading behavior. Building on this view, this thesis shows how an observed sequence of time-ordered transactions may be described and ultimately modeled as an outcome of micro-mechanisms embodying basic principles of social bonding. Examples of these social mechanisms can be defined in terms of network-like dependencies and referred to, for instance, as preferential attachment, inertia, reciprocity, and transitivity of exchange relations. Throughout the three essays that make up this dissertation, the focus is kept on reciprocity and transitive closure, two emergent social mechanisms that are usually seen as fundamental in the building of social structure and norms of collective action. All three essays in this dissertation contribute to shedding new light on a recent line of network research that emphasizes the role of social mechanisms in shaping the evolutionary dynamics of interorganizational networks. Even if these three essays represent a single empirical case, they all suggest a new theoretical interpretation of network structure as contingent and time-dependent. In doing so, this dissertation encourages future research to a more abstract reflection on network structure, which can be ultimately conceived of and understood only in terms of the network times that define the dynamics of its constitutive social mechanisms.

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Micro-mechanisms and financial markets

1.1 Motivating questions

Over the last three decades, financial markets have received considerable attention in financial economics and related disciplines ranging from sociology to physics (Lie, 1997; Lindblom, 2002; Newman, 2010). By providing insights into the structural and topological properties of financial markets, a fairly recent collection of studies on financial networks (Allen et al., 2009; Battiston et al., 2010; Zawadowski, 2013) has provided substantial examples of how graphs can represent a valuable conceptual tool to capture and study the intricate patterns of relations between financial institutions. This approach captures aspects related to some effects of network structure, like market efficiency, and allows, for example, tracking the effects of a liquidity shortage or a credit event throughout financial markets. In recent years, motivated by the emergence of multiple financial crises that have questioned the stability of financial markets as a whole, another collection of studies has focused on mapping the intertwined nature of financial markets. In this latter case, the study of financial networks has primarily focused on preventing financial distress from reverberating within fragile financial institutions (Bardoscia et al., 2017; Elliott et al., 2014), and potentially amplifying it with potentially catastrophic consequences for the entire financial system (Roukny et al., 2013). However, both streams of studies neglect to consider a crucial aspect of network analysis – namely, the process of network formation, which actually leads to the formation of interorganizational relations, the so-called market macro-structure. By shifting the focus from the effects of network structure to the process of network formation, network analysis can explain the tension between market-desirable outcomes and the actual outcomes that emerge from the links between financial organizations.

The lack of theoretical discussion on the process of network formation reminded me of Harrison White's influential article *Where do markets come from?* and triggered me to develop an equally broad question aimed at leading my research on the emergence of market structure. The question I came up with is *How do financial markets work?* Markets are typically defined in terms of aggregated quantities such as, for example, demand and supply. Another way to think of markets is as sets of concrete exchange activities (White, 1981). Beyond these obvious considerations, it is hard to find a definition of markets based on the concrete relational exchange activities that markets organize – and out of which they simultaneously emerge. Surprisingly, even the most popular microeconomics textbooks (Mankiw, 2006; Mas-Colell et al., 1995; Varian, 1992) do not provide any rigorous definition of market. The market is simply conceived as the abstract setting where two sets of agents – namely, consumers and firms – interact with the aim of pursuing their private interests. Even if it is appropriate to study the interaction between buyers and sellers through an analysis of individual decision-making (Mas-Colell et al., 1995), I think there is room for representing markets at a finer-grained scale.

To overcome the lack of theoretical discussion about the functioning of markets, I think it might be useful to recall a fundamental proposition of institutional economics in which markets are viewed as “occur[ring] naturally or spontaneously, in the sense that actors do not deliberately plan or construct them in advance of actual transactions” (Campbell et al., 1991, p.348-349). As organized institutional structures that support actual transactions, markets are suited to emerge because of a process in which connections among distinct market participants are continually reconfigured and realigned. In this

theoretical framework, markets can be referred to along three distinct, but related, meanings¹. First, markets are physical locations where economic activity occurs. Second, this activity is accomplished by market actors. Third, it is performed by applying agreed-upon rules and practices. The second and the third definition point to the fact that markets acquire their status in light of their *structure* and the *action* that they host. In more general terms, it means that markets exist not only because there are material and organizational structures that sustain them, and not only because trading occurs in those structures, but because structure and action are mutually linked in a constitutive relationship. Therefore, in order to propose a comprehensive conceptualization and understanding of markets from the above perspective, there is a need to introduce a depiction of markets that conceives of structure and action in the market not as two distinct constructions but as two characteristics of the same phenomenon.

As the empirical material of this dissertation will explain, markets in general, and modern financial markets in particular, emerge and operate while constantly crossing the boundaries between structure and action. An intuition about the accuracy of the previous statement can be developed by anyone who has ever observed a financial trading arena. The image of traders frantically auctioning securities on the bustling floor of a major trading arena, for instance, suggests that multiple means of communication, like computer screens, telephones, and face-to-face interaction, are used, and that people other than buyers and sellers are sometimes involved in the exchange process.

From the *structure* viewpoint, different types of conditions need to be satisfied in order to clear transactions (Carlton, 1989). In contrast to the neoclassical assumption that markets clear through the equation of prices and quantities, Carlton explained that, in most of the markets, clearing is achieved because of a combination between prices, quantities, and some other factors including, for example, the length of buyers and sellers' relationships and the knowledge about the counterpart's needs. This analytical trend has even expanded over the last three decades, with a growing body of research emphasizing that a variety of social mechanisms support the basic market mechanism, which guarantees the optimal allocation of resources solely according to the forces of supply and demand. The criticism of the basic market mechanism mostly reveals in proving that distinct markets exhibit different patterns of exchange behavior. Abolafia (2001)'s research on the New York Stock Exchange, for instance, has shown that the neoclassical view of profit-driven and greedy traders is far from being an accurate picture of contemporary financial markets. In the same vein, Baker (1990) has shown that traders have a preference for keeping substantially constant the panel of their trading partners. From the *action* viewpoint, financial markets emerge and contextually develop through an interaction process that evolves in continuous time.

My approach to integrating structure and action involves representing financial markets as networks of observed exchange events unfolding in continuous time. Network nodes are financial organizations that act as buyers and sellers of funds, while edges refer to the "arm's-length" ties (Uzzi, 1997) that regulate the transfer of capital. By revealing the continuous settling of prices and volumes between pairs of buyers and sellers, the collection of "arm's-length" ties can be associated with a corresponding set of dyadic, directed, and time-dependent transactions.

Along with the central tenets of Transaction Cost Economics, when taken individually, these dyadic directed transactions meet all the requirements to be the building blocks of any financial market Williamson (1985, p.1). First, transactions involving fund transfers are characterized by low *asset specificity* and, as such, are always undertaken in the market. Moreover, in case of low asset specificity, market is the preferred form of governance, whatever the degree of *uncertainty*, since bilateral depen-

¹For a comprehensive review of conceptual approaches to markets see Lindblom (2002).

dence matters little and new trading instances can be easily arranged by both parties when necessary (Williamson, 1985, p.59). Finally, when transactions occur at high frequency – as is often the case in contemporary financial markets – they warrant a persistent monitoring effort (Williamson, 1985, p. 79), in addition to the attention they naturally attract as specific objects of analysis. However, in contrast to the Transaction Cost Economics assumptions, when taken as a whole, dyadic directed transactions are interdependent through their temporal dynamics, with the obvious consequence that they exhibit inertia, namely the tendency to reproduce themselves based on their past history.

1.2 The micro-relational structure of financial markets

Conceiving of contemporary financial markets as networks of “arm’s-length” ties suggests that connections in the network develop across two layers of connection, one superimposed on top of the other. The primary level of connections is made of time-ordered sequences of transactions, while the secondary level is made of network-like dependence structures that regulate, for instance, tendencies toward repeated interaction, reciprocation, and centralization of buying and selling activities. The link between the two layers is offered by the self-organizing property (Vriend, 1995) of those exchange patterns, which emerge endogenously through the interaction among market participants and eventually crystallize in micro-mechanisms describing basic principles of organizational bonding (Laumann et al., 1978; Laumann and Marsden, 1982). The collection of such micro-mechanisms represents the so-called *micro-relational structure* of financial markets.

At a micro-level, the self-organizing property of time-ordered sequences of transactions reveals the complexity of the interaction process along multiple dimensions. First, the interplay on the floor is usually dispersed. Individual actions are significantly influenced by the expected actions of a limited set of other buyers and sellers, as well as the global state that these actors create. Second, market participants do not simply react to stimuli and responses. They indeed consistently improve their trading strategies as they accumulate experience. Third, connections are crucially influenced by the local knowledge of the identities of some potential trading partners.

At a macro-level, the self-organizing property of exchange sequences contributes to shaping the market relational structure, defined in terms of roles. In addition to the market micro-relational structure, the macro-structure of roles and relationships emerges through the interaction (Leifer, 1988) among buyers and sellers over time. In financial markets, these two roles are not preassigned. Thus, a temporal extension of the market is required to allow the system of roles to emerge. In contrast to a single transaction, which reveals nothing about actors’ roles and positions, a collection of time-dependent transactions creates a mutual obligation that naturally entails a financial market.

The novelty of the current approach to financial markets is clear. With the possible exception of a couple of studies claiming that financial markets have an underlying micro-structure corresponding with micro-networks of egocentric transactions Baker (1984) and Cohen-Cole et al. (2015), extant research has not recognized that the relational structure of financial markets emerges endogenously through sequences of time-dependent transactions connecting changing sets of buyers and sellers. From an empirical standpoint, the temporality of financial markets is perfectly captured by the time-stamped nature of some available financial datasets, like that I use in my dissertation. Finally, from a methodological viewpoint, the growing availability of continuous-time interaction data makes it possible to explicitly measure “directed behavioral event[s]” (Heise and Durig, 1997) rather than social ties typically obtained by aggregating such events over time. Such an accomplishment is particularly relevant in the context of financial markets. In fact, the observed unit of analysis, the

transaction, unfolds over fine-grained timescales of minutes or seconds, which is in stark contrast with coarse-grained phenomena like business relationships that may take months or even years to evolve.

Analyzing financial markets in light of the micro-mechanisms that emerge from sequences of time-ordered transactions suggests an interpretation of market structure that is contingent and time-dependent. On a higher level, emphasizing the temporality of market micro-relational structure posits general questions about the nature and the stability of its underlying micro-mechanisms. First, how do dyadic and extra-dyadic micro-relational mechanisms emerge under conditions of time-specificity? Second, how do they unfold over time and at what timescale? And, finally, how can a global order emerge from those self-organizing sequences of time-dependent transactions?

1.3 Reciprocation as the foundation of financial markets

To demonstrate the merit of my representation of financial markets, I narrow my analytical focus to the dynamics of reciprocation, which is intended here as the foundational micro-mechanism of financial markets. At the purely operative level, reciprocated exchange consists of the alternation of directed transactions, where i acting toward j , is followed by j acting toward i . At a more abstract level, the alternation of directed transactions is viewed as the alternation of buyer and seller roles, thus making reciprocation the main relational process underlying role-shifting.

Applicable where no specific roles are preassigned, as is often the case in financial markets, reciprocated exchange is viewed as the mechanism initiating mutually beneficial relationships (Gouldner, 1960). Market actor i gives to actor j , thus creating a pair of buyer-seller complementary roles. In doing so, i expects the norm of reciprocity to encourage j to give in return. Later, j 's giving in return does not terminate the relationship, but, in turn, prompts i to give again, and so on in a process that highlights the norm of reciprocity. In fact, when sticking to dyadic exchange, as Foster (1961, p.1185) shows “the dyadic contract is effective precisely because partners are never quite sure of their relative positions at a given moment”.

Keeping track of the process that highlights the norm of reciprocity requires focusing on its temporal component – that is, the observed delays between a pair of directed transactions involving i and j . In developing this analysis, I refer to the development of reciprocity over time by using the term *reciprocation*. Studying reciprocation as a dynamic process associated with role-shifting is important for one main reason. The delay between two directed transactions distinguishes roles and posits the basis for interpreting aggregate tendencies of exchange behavior that are independent from the role identities. This is because feelings of trust for sellers and indebtedness for buyers develop alongside role alternation and ultimately offer signals for detecting recurrent patterns of exchange. When the probability of interaction is high and the time to reciprocation is neither too quick nor too long, reciprocation naturally evolves into extra-dyadic micro-relational mechanisms that are of key importance in the functioning of decentralized markets.

On a higher level, my understanding of reciprocation as the foundation of financial markets sheds new light on the micro-mechanisms that lead to the emergence of cooperation and social cohesion – the ultimate features for having flourishing and healthy financial markets (Rubin, 2014). The surprising relevance of this generic achievement has been highlighted by recent financial crises, which have revealed that many fundamental aspects of the behavioral and structural mechanisms regulating financial markets remain poorly understood. Therefore, narrowing the analytical focus on the dynamics of reciprocation allows me to provide a principled analytical framework that connects the

observed trading behavior to the micro-relational structure of financial markets. In particular, as dyads naturally combine into triads, which in turn develop into larger structures of shared partners, examining the process of reciprocation together with extra-dyadic micro-mechanisms allows for a comprehensive understanding of the development of population-level structures.

1.4 Outline of the thesis

This dissertation adheres to the major line of network research that portrays financial markets as sets of interdependent trading relations connecting buyers and sellers of financial resources over time. My work contributes to extant studies by providing a newly derived analytical framework to connect this view to the relational structure of financial markets that emerges from observed trading behavior. Building on this view, this thesis shows how an observed sequence of time-ordered transactions can be described and ultimately modeled as an outcome of micro-mechanisms that embody the basic principles of social bonding (Laumann et al., 1978; Laumann and Marsden, 1982). Examples of these social mechanisms can be defined in terms of network-like dependencies and referred to, for instance, as preferential attachment, inertia, reciprocity, and transitivity of exchange relations.

Each essay in this dissertation examines distinct aspects related to the temporal evolution of such mechanisms. Besides the potential benefits of studying regularities in relational processes, a deeper understanding of the dynamics of interaction patterns and network evolution is seen as increasingly important (Brandes et al., 2009; Butts, 2008; Snijders et al., 2010). In this regard, available studies on financial networks (Allen et al., 2009; Battiston et al., 2010; Zawadowski, 2013) show a lack of concern and substantially confine themselves to providing structural and topological properties of financial markets. Hence, studying the link between social interaction and social relations, with a specific focus on their temporal dynamics, promises to illuminate aspects of market exchange that extant studies have overlooked.

In all three essays, the empirical value of my analysis is tested in the context of the European interbank market, a specific financial market where European banks extend loans of different maturities by channeling liquidity from institutions with surplus funds to those in deficit. The structure and functioning of interbank markets are of particular interest for studying social mechanisms that emerge from individual transactions over time. First, transactions are collected in high-frequency, time-stamped datasets that are accurate to the second. Second, the data I analyze contains detailed information on the interaction process, namely the identity of the trading banks, the value of each individual transaction, the corresponding interest rate, and the loan duration.

The empirical analysis is performed on the complete set of 504,576 overnight transactions observed over a ten-year period (2006-2015) between all 202 banks participating in the e-MID market, the only electronic market for interbank money trade in the Euro area. Even if e-MID transactions have been estimated to cover approximately the 20% of the interbank trading, they have been shown to be representative of the whole Euro interbank market (Beaupain and Durré, 2008). The choice of restricting the focus on overnight transactions – which alone account for more than 85% of all the e-MID transactions – is in line with the majority of the studies using these data and motivated by the evidence that the interbank market is mostly a market for short-term trades, where utilitarian logics of trading dominate speculative ones (Beaupain and Durré, 2008). Moreover, if loans with different maturities were included in the dataset, it would be difficult to derive representative social mechanisms that induce buyers and sellers to coordinate on the trading floor.

The first essay is entitled “Examining the temporal evolution of patterns of dyadic exchange using latent trajectories”. The study tracks how reciprocal exchange patterns have varied in response to macroeconomic events, anticipating and following the emergence of the Global Financial Crisis in 2008. The adopted methodological approach extends the model of Holland and Leinhardt (1981) to a longitudinal setting, in which individual temporal trajectories are quarterly updated and modeled through splines and node-specific parameters that measure the nodes’ differential attractiveness as buyers and sellers of liquidity. The proposed empirical application provides parameter estimates for a specific pair of actors, who mutually act as liquidity buyers and sellers in an equally balanced exchange relationship. The results provide strong evidence of significant changes in patterns of reciprocity during the observation period, indicating that the progressive emergence of the Global Financial Crisis had an impact on European banks’ preferences towards reciprocated exchange. Regardless of the illustrative example, the empirical results also show the merit of the adopted methodological approach, which is capable of investigating both systematic changes and inter-individual variability in exchange behaviors.

The second essay is entitled “From ties to events in the analysis of exchange relations: the emergence of network times”. The theoretical premise that underlies this study is that a significant amount of information is lost when aggregating time-stamped data into binary network ties observed at discrete time points. In this regard, this study demonstrates that, when maintaining the natural timing of the interaction process, the social mechanisms that emerge from time-ordered sequences of transactions possess their own internal timing, which accurately reflects the variations in high-frequency relational activities underpinning network ties. By focusing on the dynamics of reciprocity and transitive closure, the empirical part of the study suggests that the sequence and timing of transactions have profound importance for discriminating among the time frames in which different social mechanisms unfold. Moreover, the comparison between the internal time distribution of reciprocity and transitive closure shows that distinct social mechanisms do not operate in synchrony, and do not depend on their history in the same way because of the sequential constraints they are subject to (Abbott, 1990; Chase, 1982; White, 1970).

The third essay is entitled “Effects of market uncertainty on exchange structures”. The study employs a quasi-experimental research design, informed by recent financial crises, to identify discrete time periods corresponding to market-level shifts in exchange regimes and to examine period-specific variations in network-based social mechanisms of contingent interest. On the one hand, the empirical application focuses on the role of reciprocated exchange as a major uncertainty-reduction strategy in the presence of partner selection. On the other hand, the analysis investigates the contextual role of transitive closure as a signal that banks adopt to convey information about their creditworthiness. The essay also introduces a newly derived specification for a relational event model (Butts, 2008) inspired by the original work of Vu (2012) and adapted to incorporate the distinction between short- and long-term social mechanisms. On the one hand, parameter estimates for reciprocity show that while short-term tendencies to reciprocated exchange weakened during the turmoil period of the crisis, the corresponding long-term counterparts became stronger. On the other hand, parameter estimates related to transitive closure suggest that transitivity is a more time-sensitive social mechanism, which activates solely in longer time horizons. Together, these results underscore the importance of considering sequences of interactions across different time frames and ultimately examining the organizing principles underlying the short- and long-term temporal regularities of interaction.

Overall, all three essays in this dissertation contribute to shedding new light on a recent line of network research that emphasizes the role of social micro-mechanisms in shaping the evolutionary dynamics of interorganizational networks (Powell et al., 2005; Rosenkopf and Padula, 2008). Even if

these three essays represent a single empirical case, they all suggest a new theoretical interpretation of network structure as contingent and time-dependent because of the constraints imposed on current relational activities by the “network of other cases and prior times” (Abbott, 1995, p.94). In doing so, this dissertation encourages future research to take a more abstract approach to network structure, which can ultimately be conceived of and understood only in terms of the network times that define the dynamics of its constitutive social mechanisms.

The European interbank market

2.1 Market overview

Interbank markets channel liquidity from institutions with surplus funds to those with deficits, with the fundamental goal of mitigating the propagation of defaults between banks embedded in networks of liabilities. That being said, the European interbank market enables European banks to lend to one another for two primary purposes. First, satisfying banks' liquidity financing needs with the aim of managing anticipated and non-anticipated short-term liquidity imbalances. Second, the reserve requirements imposed by the European Central Bank (ECB) must be fulfilled with the aim of promoting suitable liquidity management programs. The effects of transactions taking place on the European interbank market have an immediate extension to the global economy. For instance, variations in interbank rates are rapidly transmitted throughout the entire term structure, thereby affecting borrowing conditions for both firms and households. Indeed, in addition to LIBOR, Euribor, and EONIA, interbank rates serve as benchmarks for pricing fixed-income securities. Moreover, interbank rates underlie derivative contracts, such as interest rate swaps or short-term interest rate futures, which are commonly used by financial institutions to hedge against variations in short-term interest rates. Therefore, for all of these reasons, a well-functioning interbank market is the premise for central banks to efficiently trade liquidity, achieve the desired level of interest rates, and eventually transmit monetary policy.

A detailed description of the European interbank market can be specified by referring to some of its distinctive features, namely:

- the financial instruments implied to transfer funds among banks;
- the market where fund exchange takes place;
- the presence of a third non-bank party involved in the exchange;
- the type of relationship connecting two counterparts;
- the bank residence.

First, with respect to the implied financial instruments, the European interbank market is composed of two large and distinct segments: the *money market* and the *other interbank market*. On the one hand, the *money market* implies the use of both unsecured (deposits and certificates of deposits) and secured instruments (repos). On the other hand, the *other interbank market* implies the use of bonds and derivative contracts. Second, with respect to the marketplace where transactions take place, the exchange of funds occurs either on regulated or unregulated *over-the-counter* (OTC) markets. While OTC transactions ensure participants' anonymity, the actual conditions of regulated transactions are fully available. Third, with respect to the absence or presence of a third non-bank counterpart, interbank transactions can be carried out bilaterally – as it always happens in the OTC market – or through a central counterpart that mediates the lending operations between two banks. Fourth, with respect to the type of relationship connecting two counterparts, transactions can be intra- or extra-group. Finally, regarding the nationality of the counterparts, transactions can be both domestic and cross-border.

Among all segments that make up the entire market, the interbank *money market* plays a crucial role in the transmission of monetary policy impulses, which are propagated by reallocating the liquidity originally supplied by the national central banks. A fundamental reason for this reallocation is the need to provide a heterogeneous banking sector with easy access to liquidity. In fact, when borrowing from the central bank, financial institutions face different costs based on adequate collateral. Alternatively, when borrowing on the interbank *money market*, and especially on the market for unsecured loans, banks do not face the cost of holding eligible assets. Therefore, thanks to the European interbank market, all the financial institutions operating in the Eurosystem have facilitated access to liquidity.

In the interbank money market, financial instruments are traded as cash equivalents, and approximately 90% of liquidity contracts are regulated *overnight*, the shortest possible term loan. When involved in an overnight loan, the borrower has to pay back the borrowed funds – plus the charged interest rate – at the beginning of the next trading day. Given the short period of the loan, the overnight rate is, generally speaking, the lowest rate at which banks lend their excess liquidity. Most of the activity in the overnight market occurs in the morning, right after the start of business, when banks forecast their clients' liquidity needs for that day. If banks' analysts expect their clients to need more liquidity than the institution has on hand, then the institution will borrow money on the overnight market that day. Conversely, the institution will lend money on the overnight market that day. However, the bank can enter into new credit contracts at any time to meet clients' unexpected requests.

Besides its relevance in terms of size, the analysis of the overnight segment is crucial for understanding the entire trading dynamics of the European interbank market. First, thanks to high-frequency transactions, the overnight market absorbs short-term liquidity shocks and progressively adjusts the liquidity positions of credit institutions. Second, and more importantly, in short-term loans, utilitarian motivations to trade prevail over speculative ones, thus reinforcing the relationships among credit institutions. Both of these features make the overnight segment of the European interbank market an ideal empirical setting for investigating the emergence and development of a distinct structure of exchange that arises from the collection of high-frequency transactions.

2.2 Networks of credit relations

Over the last ten years, a substantial body of literature has provided numerous examples to demonstrate how networks can represent a valuable conceptual framework for capturing the intricate patterns of connections between financial institutions (Allen and Babus, 2008; Battiston et al., 2010; Zawadowski, 2013). By investigating a wide range of phenomena related to the analysis of credit relations in local interbank markets, financial economists have extensively legitimized interbank markets as a suitable empirical setting for examining the complexity of exchange relationships. For instance, Cocco et al. (2009) have investigated the nature of credit relationships in the fragmented Portuguese interbank market over the period 1997-2001. The authors have shown that frequent and repeated money transfers between the same banks occur with a probability higher than that expected for random matching, thus indicating that credit institutions are prone to maintaining credit relationships with established trading partners. This finding suggests that banks carefully select their trading partners with the aim of reducing dependence and increasing the efficiency of their transactions. Moreover, Cocco et al. (2009) have shown that favorable interest rates go along with preferential

lending as a reward for a durable and transparent credit relationship. Finally, more recently, Affinito (2012) have found the same empirical evidence by analyzing interbank relationships among Italian banks. Altogether, former studies on local interbank markets reveal that, rather than shopping for better prices, banks are more likely to develop stable banking relationships and activate them where necessary.

Starting from the mid-2000s, a collection of studies on financial networks has been providing a detailed descriptive analysis of empirical regularities and mathematical properties that characterize the network of overnight liabilities between banks in the Euro area. Boss et al. (2004), for instance, have explored the network of lending relationships in the Austrian interbank market and provided empirical evidence for a power-law distribution of contract sizes and a power-law decay of incoming and outgoing links. De Masi et al. (2006) and Iori et al. (2007) have studied the Italian interbank market and investigated the mechanism driving the formation of clusters. In the same empirical setting, Iori et al. (2008) have shown that the Italian interbank market exhibits a fairly random network at the daily scale. Interestingly, non-random structures have been proven to emerge for longer aggregation periods. Monthly and quarterly aggregated data reveal, for instance, that, since the 1990s, the network of credit relationships includes a tightly connected core of banks acting as global hubs for the whole network (Iazzetta and Manna, 2009).

More recently, increasing attention has been devoted to studying the entire European interbank market and analyzing the network mechanisms that lead to the emergence of preferential trading patterns. By using a methodology based on the detection of statistically validated networks, Tumminello et al. (2011) and Iori et al. (2015) have modeled an agent-based interbank market that reproduces some features of preferential trading patterns. Furthermore, as Finger et al. (2013) and Fricke and Lux (2015) have suggested, those preferential trading patterns go along with some stylized facts, such as dissortativity and proximity to a core-periphery structure. More precisely, from this body of work emerges the key idea that a lender is more prone to lend to borrowers it has lent to in the past rather than to other borrowers with which the lender has never – or infrequently – interacted. Down to the path paved by Iori et al. (2015), Hatzopoulos et al. (2015) have shown that preferential trading between banks is primarily driven by the heterogeneity of the banks. Along the same line, Finger and Lux (2017) have introduced a stochastic actor-oriented model (SAOM) with a large number of network-related effects, actor-specific and dyadic variables as potential determinants of banks' link formation in the interbank market.

All of these findings indicate that the European interbank market is a highly structured network where exchange exists not only in terms of discrete transactions, but also in terms of ongoing business relationships (Granovetter, 1985) that determine individual and collective outcomes (Granovetter, 1992). All the reviewed studies emphasize how distinct forms of preferential attachment lead to the emergence of peculiar network structures. However, none of them has ever investigated the relational structure of the European interbank market, thus explaining how dyadic coordination between a pair of buyers and sellers is achieved and, eventually, evolves over time.

2.3 Data source: The e-MID trading platform

Keeping the focus on the entire European interbank market, the most prominent example of a regulated *money market* is e-MID, the only electronic market for interbank deposits in the Euro and US

areas.¹ The e-MID market was founded in Milan in 1990 for Italian Lira transactions and became denominated in Euro in 1999. Since then, the e-MID's trading activity has been supervised by the Bank of Italy. The e-MID market is based on a real-time gross settlement system called TARGET2², owned by the Eurosystem, and accessible to all banks operating in the Euro area – that is, banks from Austria, Belgium, Switzerland, Germany, Denmark, Spain, France, United Kingdom, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Poland, and Portugal. Thanks to its preferential lane in TARGET2, liquidity can be available at a low price and managed flexibly. Availability of liquidity and its low price are assured by the reserve maintenance system operated by the ECB, consisting of a time frame of approximately six weeks in which credit institutions must maintain a specified level of funds calculated on the basis of banks' balance sheets before the start of the maintenance period. In particular, the availability of liquidity is ensured by allowing credit institutions to utilize fully remunerated minimum reserves. A low price is instead supported by enabling credit institutions to make use of averaging provisions. Summary statistics referring to minimum reserve requirements and liquidity conditions are published annually and quarterly on the basis of the last maintenance period of the year and quarter, respectively.

Actually, the e-MID market resembles a multilateral screen-based trading platform where banks can electronically transfer interbank deposits by adhering to market regulations. Once registered on the platform, banks are admitted to trading activities. The Euro segment is active from 7:00 to 18:30. The half-hour period between 18:00 and 18:30 is the so-called *cut-off close period* for the overnight segment and represents the last opportunity to place orders that need to be executed on the same day. Duration-wise, credit contracts have a wide range of maturities spanning from one day to one year. Size-wise, for some maturities traded on the market, the platform distinguishes between *regular* transactions – with a minimum amount of EUR 1.5 million – and *large* transactions – with a minimum amount of EUR 100 million. However, such a distinction is not so strict, especially for regular overnight transactions. In this latter case, it is not infrequent to find some regular classified trades with amounts either lower than EUR 1.5 million or greater than EUR 100 million.

The e-MID market is a quote-driven trading platform. Trades are public in terms of duration, amount, rate, and time. Market participants willing to trade can make their interest public to their counterparts by acting as *quoters* and proposing the setting of the loan contract. If the deal attracts a counterpart, this last acts as an *aggressor* by sending the order back to close the deal – which adheres to the features specified in the request (Fig. 2.1). On the one hand, when a bid proposal is hit, it is automatically executed. On the other hand, when an ask proposal is hit, it requires a credit line check before the order is manually accepted. A *quoter* can select one or multiple specific quoters by sending *request for quotes*. However, if *aggressors* do not find the deal attractive, they can reject the aggression.

Transactions on the e-MID market are collected in time-stamped datasets in which each line reports the distinctive features of the corresponding loan contract. Transactions typically occur every few seconds, and the exact timing corresponding to the money transfer is accurately recorded. In revealing their intention to trade on the e-MID platform, *quoters* and *aggressors* make their identity visible to their peers. However, the data collection process obscures the identity of banks trading on the e-MID market from the public. Banks' identities are replaced by a unique identification code that reveals only the banks' nationality. This data restriction, unfortunately, makes it impossible to

¹<http://www.e-mid.it/index.php>

²<https://www.ecb.europa.eu/explainers/tell-me/html/target2.en.html>

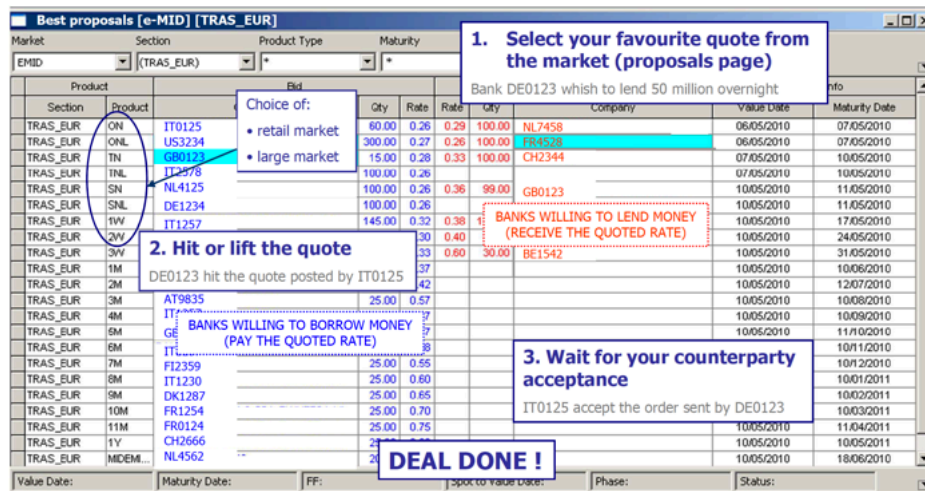


Fig. 2.1: Trading mechanism on the e-MID platform

match e-MID trading data with banks' balance sheets and acquire other banks' specific data. In the available data, any *aggressor* is characterized by referring to the market side of its aggression. Banks that lend money are associated with a *sell* label. Accordingly, banks that are in need of borrowing money are associated with a *buy* label. The exchanged amount – expressed in millions of EUR – the corresponding interest rate, and the duration specified in the contract are also reported in the public data (Fig. 2.2).

While trading on the e-MID platform is not affected by a lack of transparency or search frictions, it is influenced by its own specific micro-structure. Baglioni and Monticini (2008), for instance, have shown the presence of an intraday term structure of interest rates, with banks borrowing at a premium early in the morning and at a discount at the end of the day. Instead, Gabbi et al. (2013) have found that, due to bid-ask spreads, both lenders and borrowers are able to obtain better rates when they act as quoters rather than as aggressors.

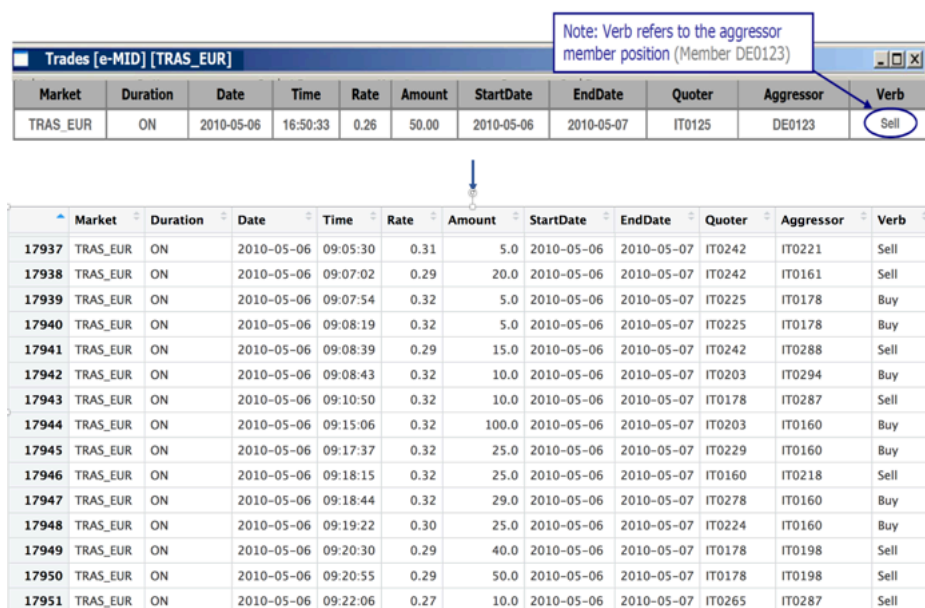


Fig. 2.2: Distinctive features of e-MID's credit contracts

I collected data on the e-MID trading platform over a ten-year period, from January 2006 to December 2015. In line with the reviewed studies, I restrict my analysis to the overnight segment, which accounts for approximately 90% of all e-MID transactions. Since the interbank market is primarily a market for short-term trades, including loans with different maturities in the dataset could result in a biased picture of the market dynamics. The resulting dataset comprises a time-ordered sequence of 504,576 loan contracts between 202 banks from 16 different countries. The sample at hand includes the *Global Financial Crisis* (GFC), which was preceded by a period of turmoil that began in summer 2007 and fully developed after the collapse of Lehman Brothers on September 15, 2008. Eventually, the GFC led to the *Sovereign Debt Crisis* (SDC) in spring 2010 (Drudi et al., 2012), when the newly elected Greek government ordered an audit of public finances. The findings were shocking, and this caused tensions in the sovereign debt market. Financial market concerns about the sustainability of Greek public finances were exacerbated, rendering the measures of local governments to support their banking sectors and counter the economic slowdown largely ineffective. From May 2010 onward, similar concerns emerged regarding Irish, Portuguese, and later Spanish and Italian public finances, negatively impacting market liquidity invested in new and existing sovereign debt. Therefore, the quasi-experimental nature of the data allows for the division of the entire sample into four distinct subsamples, corresponding to four distinct financial phases or exchange regimes. The range boundaries of each phase are related to the development of the Global Financial Crisis and can be summarized as follows:

Tab. 2.1: Financial phases across the whole observation period

Period	Description		Key date
01 Jan 2006 – 08 Aug 2007	Stability	08 Aug 2007	BNP Paribas' funds freeze
09 Aug 2007 – 14 Sep 2008	Turmoil		
15 Sep 2008 – 07 May 2010	GFC	15 Sep 2008	Lehman Brother's collapse
08 May 2010 – 31 Dec 2015	SDC	08 May 2010	Audit of Greek public finances

Splitting the whole period of observation into four distinct financial phases as suggested in Tab. 2.1 sticks to the timeline of the financial crisis proposed by Drudi et al. (2012) – the first and only study outlining the mutating nature of a systemic financial crisis “that is unprecedented in terms of financial losses, and fiscal costs, geographic reach, and speed and synchronisation” (Drudi et al., 2012, p.1). Setting the boundaries of the Global Financial Crisis is an arbitrary choice, mostly shaped “with the benefit of hindsight” (Drudi et al., 2012, p.3). However, the proposed classification is the only option available for the empirical setting under analysis, as evidenced by the increasing number of studies that have appeared in peer-reviewed scientific journals (Gabbi et al., 2013; Hatzopoulos et al., 2015; Temizsoy et al., 2015).

During the turmoil and the Global Financial Crisis period, certain European banks faced financial distress. However, the overall economic system held together. On the one hand, such a positive outcome is attributable to the application of standard measures “to tackle the increasing loss of confidence, jumps in risk aversion, and resulting malfunctioning of various financial market segments” (Drudi et al., 2012, p.4). On the other hand, multiple drawbacks are associated with such support measures. First, prior to the onset of the crisis in August 2007, lending conditions were largely set regardless of borrowers' creditworthiness. However, things abruptly changed after the insolvency of Lehman Brothers. Widespread concerns have rapidly mounted, resulting in a freeze in the European interbank market – a situation that hinders the liquidity reallocation process, even for healthy credit

institutions. Accordingly, the whole market has progressively contracted, as Fig. 2.3 and Fig. 2.4 show.

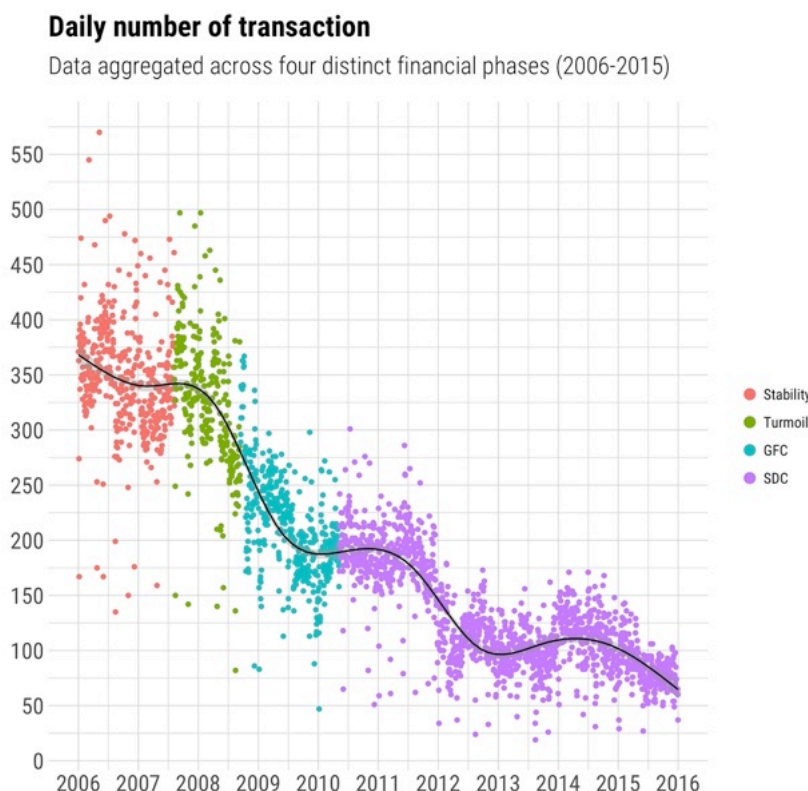


Fig. 2.3: Number of daily transactions across four distinct financial phases

Another relevant change that affected the European interbank market after August 9, 2007, was the increased awareness of counterparty credit risk, leading to a severe widening of money market spreads between the unsecured interbank offered rates and the secured overnight interest swap rates. As Angelini et al. (2011) and Drudi et al. (2012) have explained, the increased awareness of counterparty credit risk played a key role in determining the downward pressure on unsecured rates (Fig. 2.5). In fact, in the presence of a confidence crisis, there was an immediate tendency toward liquidity hoarding, which naturally led to an increase in the ECB's balance sheet that, in turn, mechanically pushes the interest rate on overnight deposits downward and closer to the interest rate on the ECB's deposits.

The anomalous crisis development since August 2007 has highlighted the extent to which banks have relied on short-term funding in the money market. In contrast to past beliefs, it became immediately clear that the *money market* segment of the European interbank market could experience a breakdown of trading like any other market. However, as the study by Angelini et al. (2011) has shown, banks' features, such as credit ratings, capital ratios, or profitability, remained substantially stable during the turmoil and the GFC periods. What has significantly changed in the market is the number of active trading banks counterparts and the trading activity, as Fig. 2.6 and Tab. 2.2 show.

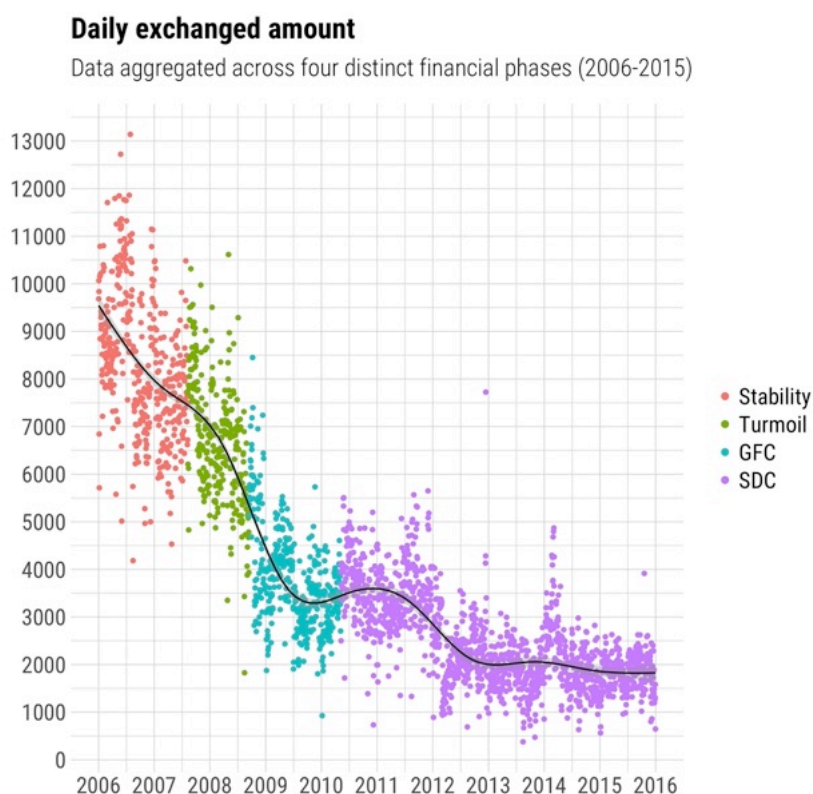


Fig. 2.4: Daily traded amount across four distinct financial phases

To test whether the identified four financial phases and the corresponding cutting dates are significant in my sample, A Bai and Perron test (Bai and Perron, 2003) was applied for the simultaneous estimation of multiple breakpoints on the same quantities of interest. In all four financial phases, at least four breakpoints have been selected for the three measures of interest, namely the number of daily transactions, the daily exchanged amount of liquidity, and the daily average interest rate. For all three selected variables, Tab. 2.4 shows that all the breakpoints are situated reasonably close to the breaking dates proposed by Drudi et al. (2012), thus confirming that the adopted timeline of the Global Financial Crisis is a good choice for the dataset at hand. With most breakpoints concentrated in the SDC phase, the impact of the ECB's exceptional measures to support the global banking sector becomes apparent. Moreover, interestingly enough, it emerges that the number of daily transactions and the daily traded amount, along with the daily interest rate, promptly reacted to and anticipated the shocks from Lehman Brothers and BNP Paribas, respectively.

From a statistical viewpoint, it appears that something also occurred between 2012 and 2014. Ireland followed Greece in requiring a bailout in November 2010, with Portugal following in May 2011, along with Spain and Cyprus requiring official assistance in June 2012. From an economic viewpoint, however, this chain of events do not define a new financial phase.

Recent papers have shown that studying the interbank money market during the crisis is a worthwhile exercise for understanding the intertwined patterns of market dynamics. Hatzopoulos et al. (2015), for

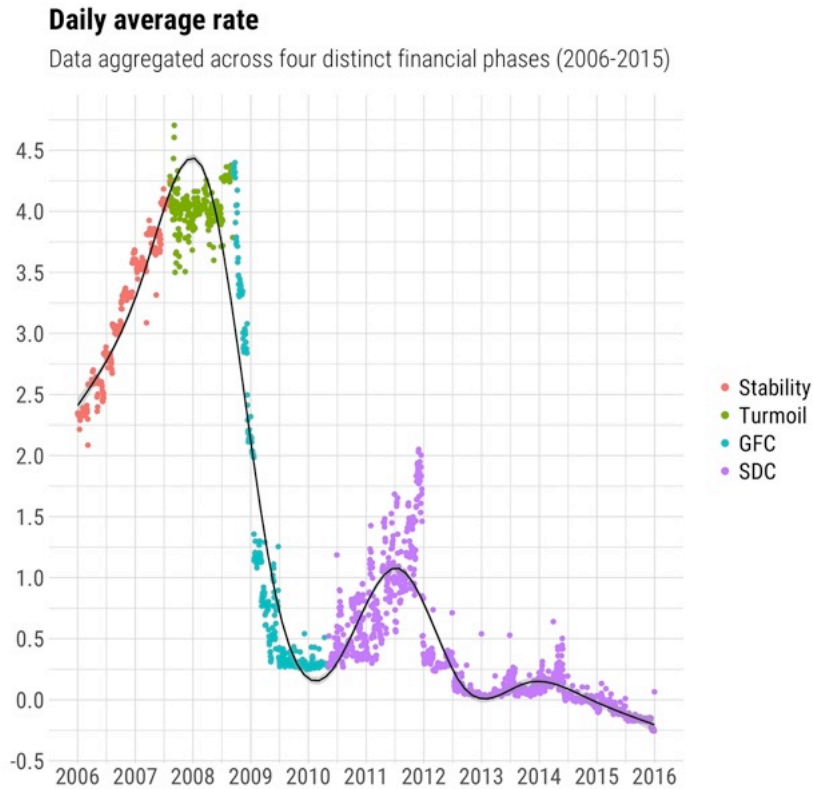


Fig. 2.5: Average daily rate across four distinct financial phases

example, have studied the temporal evolution of the matching mechanism among liquidity providers and borrowers. Their study has revealed that during the crisis, banks are more likely to be chosen as trading partners if they are active traders. Fricke and Lux (2015) have investigated changes in the topology of interbank networks as a consequence of major structural changes like those induced by the subprime crisis. Their analysis has shown that the e-MID network underwent an abrupt topological change in 2008, thus providing a clear, but unpredictable, signal of the crisis. In the same vein, by using data collected on the Dutch interbank market, Squartini et al. (2013) have shown that gradual changes in dyadic and triadic motifs provided evidence of early warning topological precursors as early as 2005. Affinito (2012), Temizsoy et al. (2015), and Bräuning and Fecht (2016) have shown that preferential lending relationships increased during the crisis, with both lenders and borrowers having benefits in terms of access to liquidity and funding rates.

2.4 Relevance of the empirical setting

A major line of network research depicts financial markets as complex relational systems (Baker, 1984, 1990; White, 1981), that is, a set of interdependent trading relations connecting buyers and sellers of financial resources over time. Although longitudinal analyses of financial networks are well-documented among the aforementioned studies, none of them has explained why the emergence of the Global Financial Crisis is fundamental for a deeper understanding of the behavioral and structural

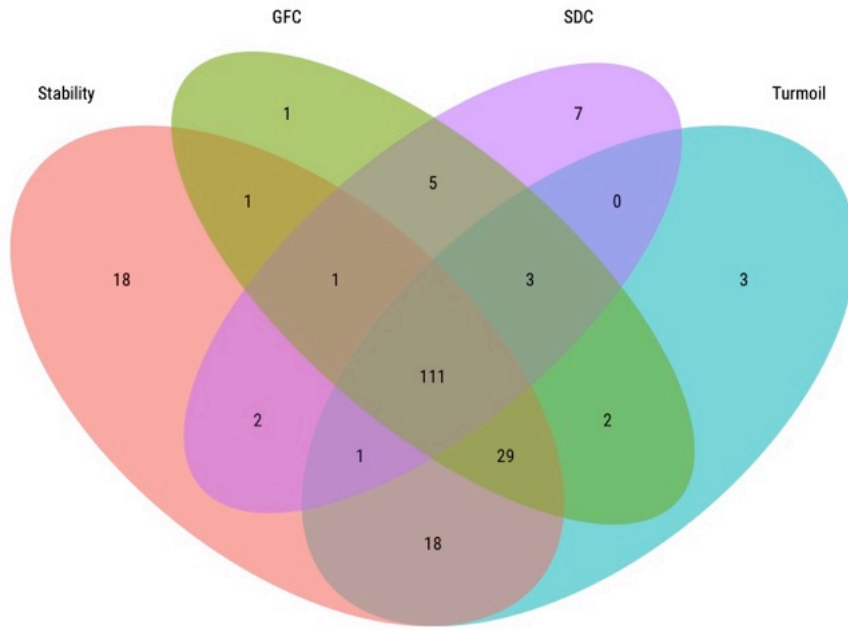


Fig. 2.6: Number of actors across four distinct financial phases

mechanisms regulating financial markets. However, more importantly, none of them has explained why the European interbank market is an ideal setting for connecting this view to the relational structure of financial markets emerging from transactions observed in continuous time.

I analyze the European interbank market as a time-ordered collection of dyadic and directed transactions among banks, here simply conceived as organizations. Taken individually, these transactions are viewed as relational events (Butts, 2008). As a whole, they crystallize into micro-relational mechanisms that ultimately give rise to the so-called *micro-relational structure* of financial markets, which develops over time according to the self-organizing properties of the corresponding relational events. Clearly, my idea of market micro-relational structure as induced by micro-mechanisms arising from time-dependent sequences of relational events is perfectly reflected by the trading mechanism adopted on the e-MID platform (Fig. 2.1). Moreover, the time-stamped nature of e-MID data enables the study of banks' trading behavior by focusing on transactions – the building blocks of any market – and characterizing the relational mechanisms through their temporal component. This achievement is of particular relevance in the context of interorganizational networks, in which the effects of distinct social mechanisms on the structure of interorganizational networks are usually assumed not to change over time, or change only because of exogenous shocks (Corbo et al., 2016). In fact, with the possible exception of recent studies that distinguishes between short- and long-term effects of reciprocity (Kitts et al., 2017; Quintane et al., 2013) and transitive closure (Quintane et al., 2013), studies on interorganizational networks implicitly keep assuming that the effects of distinct social mechanisms remain constant over time, and that they operate in synchrony. Finally, the interbank market, like most financial markets, is an example of *switch role-market* (Aspers, 2011) – that is, a market where the same actor can stay on opposite sides of the market interface, thus acting both as a buyer and seller. Thus, switch-role markets are an ideal empirical setting to test the emergence of reciprocation,

Tab. 2.2: e-MID's summary statistics by year

	Number of transactions	Number of actors	Volume (Billion EUR)	Daily average volume	Daily average rate
2006	90368	172	2228038.15	24.82	2.83%
2007	86447	170	1908744.24	22.30	3.87%
2008	75931	157	1510761.43	20.01	3.82%
2009	52742	137	917264.41	17.49	0.63%
2010	49228	127	902764.25	18.36	0.44%
2011	28381	100	583891.51	20.89	0.21%
2012	28381	100	583891.51	20.89	0.21%
2013	24839	90	462948.24	18.77	0.08%
2014	28808	90	535749.33	18.51	0.08%
2015	21488	78	467564.72	22.25	-0.11%

Tab. 2.3: Bai and Perron (2003) test for the estimation of multiple breakpoints

	Stability	Turmoil	GFC	SDC
Daily number of transactions			2008.10.15	2010.05.28 2011.12.19 2014.07.03
Daily exchanged amount	2007.07.03		2008.12.31	2012.02.29 2014.05.27
Daily average interest rate	2007.07.03		2008.12.31	2010.07.09 2012.01.02 2014.06.11

Tab. 2.4: Bai and Perron (2003) test for the estimation of multiple breakpoints

the foundational mechanism of connected markets. In fact, in markets where there is a likelihood of repeated interaction, reciprocation is the necessary mechanism for more complex dependence structures to emerge and for binding together a trading arena where utilitarian reasons to trade prevail over speculative ones. To conclude, from a methodological viewpoint, the increasing availability of time-stamped data makes it possible to test newly derived versions of ad hoc relational event models, especially designed to model large samples of continuous time interaction data.

Examining the temporal evolution of patterns of dyadic exchange using latent trajectories

3.1 Introduction

Markets can be represented as networks, where buyers and sellers are nodes and transfers of financial resources are represented by edges. To capture how market participants relate to their trading counterparts, we focus on dyadic exchange, the most immediate construct that shapes the interaction patterns between a pair of buyers and sellers. In a study on dyadic exchange, the focus is on the collection of dyads that exist among a set of actors and the relations defined on the pairs of actors (i, j) (Wasserman and Faust, 1994). In this regard, dyads can be classified into four groups. First, dyads refer to a reciprocal relationship between node i and j , existing when i transfers resources to j ($i \rightarrow j$) and vice versa. Second, asymmetric dyads, which can occur in two ways: either i transfers resources to j ($i \rightarrow j$) or j transfers resources to i ($j \rightarrow i$), but not both. Finally, null dyads, in which neither actor has a tie to the other.

Among the four types of dyadic exchange, we show particular interest in reciprocal dyads. The first reason for our interest is that, without neglecting asymmetric and null dyads, it is the norm of reciprocity that ultimately guides social interaction over time (Blau, 1964; Emerson, 1976; Gouldner, 1960). At a macro-level, as a specific form of dyadic network dependence or influence, reciprocity operates as a conflict resolution tool (Powell, 1990), as an uncertainty reduction strategy (Uzzi, 1996), and as a promoter of trust and cohesion (Friedkin, 2004; Molm et al., 2007, 2012). At a micro-level, as a dynamic mechanism emerging from repeated exchange, reciprocity has received less attention (Brandenberger, 2018; Kitts et al., 2017; Quintane et al., 2013). In this regard, our study offers a fine-grained representation of the reciprocal exchange dynamics in connection with unobserved (latent) trajectories of dyadic exchange. The second reason why we are interested in the temporal dynamics of reciprocal exchange is specific to financial markets. On one hand, reciprocal exchange emerges in longitudinal settings, when a transfer of capital from i to j is followed by another transfer of capital in the opposite direction at a later time. On the other hand, reciprocal exchange only emerges in the so-called *switch-role markets* (Aspers, 2011) – that is, markets where participants i and j generically act as traders with one another, thus encompassing the roles of buyers and sellers. When actors i and j do not permanently take the role of either buyer or seller, their participation in the market can be measured by referring to their propensity to take distinct roles within a specific time window. Since reciprocity develops contextually to role-fluidity, the strength of a trading relationship between i and j at time t can be measured by referring to distinct sets of parameters: those measuring the amount of reciprocity between nodes, and those related to the node differential attractiveness as buyer and seller.

A substantive example of a switch-role market rich in reciprocated transactions is the one analyzed in the present study, the European interbank market, where banks trade liquidity on a daily basis by channeling funds from institutions with surplus to those in deficit. Most banks active on the

interbank market can enter into new credit contracts as lenders or borrowers by simply referring to their contingent liquidity needs, rather than adhering to preassigned institutional roles. In this particular setting, a reciprocal exchange is observed when a money transfer from i to j is followed by a new money transfer in the opposite direction in the same time window.

We collected interbank transactions as they occurred on the e-MID trading platform over a ten-year period, from January 2006 to December 2015, including the Global Financial Crisis in 2008. The estimation of dyadic exchange temporal patterns is of great relevance during the observation period. The European interbank market, in fact, has experienced severe changes (Frutos et al., 2016) since summer 2007, when a period of great market turbulence preceded the onset of the Global Financial Crisis, which started immediately after the Lehman Brothers' collapse. While in normal times the interbank market has served as the main venue for banks to access short-term financing, in dysfunctional times it has experienced a market seize up that produced malicious effects on credit availability and ultimately induced the European Central Bank (ECB) to inject the market with a collection of measures designed to provide banks with the access to short-term loans. Due to the richness of economic scenarios during the observation period, the longitudinal modeling approach we propose enables us to pursue two distinct yet related goals. First, investigating whether an exogenous market shock causes the emergence of new exchange patterns, alongside the repetition of past trades. Second, investigating whether distinct patterns of exchange anticipate or adjust to that exogenous shock, once it has occurred.

The estimation of temporal patterns of dyadic exchange adopted in this paper is based on the pioneering work of Holland and Leinhardt (1981) that introduces log-linear models for binary networks. More precisely, we restrict our attention to the so-called p_1 model, based on main effects accounting for the general tendency to relate with other units and second-order effects for the tendency to establish relations and reciprocate them. Our model features a longitudinal extension based on latent trajectories, thereby emphasizing the stability and change of individual behavioral patterns over time. In particular, we consider a sequence of time intervals and, for each of them, we assume, for the dyads, a log-linear model based on individual main effects and time-specific second-order effects. These effects are assumed to follow trajectories that are based on splines of a suitable order and individual-specific parameters. Therefore, as output from the model, we obtain individual-specific trajectories for the tendency to relate with each one of the other specific units and an overall trajectory for the tendency to connect with others and reciprocate their actions. This type of longitudinal extension is of particular interest when the representation of such trajectories enhances the overall understanding of temporal patterns within a period that includes specific macro events or exogenous shocks, as in our application. At least to our knowledge, this type of extension – which is different from a transitional formulation based on modeling the behavior of actors in each period given previous periods – is new in the social network and statistical literature. For a thorough overview of latent trajectory models, see, among others, (Bollen and Curran, 2006).

Our attempt to extend Holland and Leinhardt (1981), however, is not isolated. In fact, over the last thirty years, many extensions of the basic p_1 model have been proposed with the aim of providing adequate models and estimation methods for the analysis of categorical network data. Right after the publication of Holland and Leinhardt (1981), the authors themselves suggested some directions for future work. For instance, they highlighted the importance of utilizing nodal attributes or available covariates in the analysis of network data. In this regard, Fienberg and Wasserman (1981) classified nodes into distinct subgroups based on categorical attributes and assumed the parameters of the p_1 model to be equal for nodes in the same subgroup. This extension paved the path to stochastic block-modeling, later developed by Holland et al. (1983) and Wang and Wong (1987). More recently,

Van Duijn et al. (2004) proposed a random-effects model that uses both nodal and dyadic attributes to estimate reciprocity and attractiveness parameters. Extensions of Holland and Leinhardt (1981) to deal with multiple network relations have been provided by Fienberg et al. (1985). In the same vein, Wasserman and Galaskiewicz (1984) and Wasserman and Iacobucci (1986) proposed models for analyzing network data based on valued relations.

The doubtful assumption of dyad independence behind the p_1 model has been originally questioned in Fienberg et al. (1985) and in Wong (1987)’s Bayesian version of this model. With a similar purpose, Frank and Strauss (1986) introduced a log-linear model for graphs with Markov dependencies between dyadic and extra-dyadic network structures involving the same actors. Among others, the mentioned Markov random graphs of Frank and Strauss (1986) and especially the estimation procedure proposed for these models (Strauss and Ikeda, 1990) opened up to a new generation of network models started with the p^* model of Wasserman and Pattison (1996) and ended up with the formulation of the so-called Exponential Random Graph Models (ERGMs) (Robins et al., 2007; Snijders et al., 2006; Wang et al., 2009).

Longitudinal extensions of the log-linear approach have been initially proposed by Wasserman (1987) and Wasserman and Iacobucci (1988) for two and multiple time points, respectively. Both models assume independence among dyads. However, the latter distinguishes between associative and predictive models: While associative models specify, for each dyad (i, j) , complex association patterns between the time-dependent values, predictive models define the conditional distribution of a dyad at each given time point, assuming its history as given. In this regard, our approach is a more efficient reparameterization of the model in Wasserman and Iacobucci (1988): with the introduction of fixed and random effects, we still have a model which is easy to interpret, and at the same time, we are able to significantly decrease the number of parameters to estimate. Therefore, the methodology becomes applicable to datasets with a realistic number of time periods and to large networks. Moreover, we also enlarge the framework of Wasserman and Iacobucci (1988) to the presence of edge covariates, and propose an efficient iterative numerical algorithm for composite pairwise likelihood estimation (Lindsay, 1988; Varin et al., 2011), based on all ordered pairs of units.

The proposed model also differs from other models for longitudinal network data, such as Stochastic-Actor Oriented Models (SAOMs) (Snijders, 1996) and Temporal Exponential Random Graph Models (TERGMs) (Hanneke et al., 2010; Krivitsky and Handcock, 2014; Lee et al., 2017) that may be used to study dyadic and extra-dyadic dependencies on complete networks. While our model narrows the focus to dyadic structures of network dependence, it captures all the possible forms of dyadic dependencies regardless of whether nodes are actually connected or not.

From a different perspective, our model also contrasts with more recently developed continuous-time network models (Hunter et al., 2011; Perry and Wolfe, 2013; Vu et al., 2011), which are primarily based on survival and event history analysis and focus on structured sequences of relational events (Butts, 2008) observed in continuous time. With respect to this class of models, dynamic latent trajectory models focus on discrete-time networks or discrete realizations of a continuous process (e.g., Durante and Dunson, 2014), which are summarized by a collection of cross-sectional snapshots of the network sampled at discrete time points.

3.2 The model

We propose a longitudinal modeling framework for relational data based on latent trajectories. We model dyadic interactions by using a newly derived version of the basic p_1 model introduced by Hol-

land and Leinhardt (1981). Our model conceives actors as selecting their trading partners among a variable set of potential counterparts. The observational dependence between transactions is determined by endogenous dyadic network structures that express tendencies toward reciprocity and differential attractiveness of each node.

3.2.1 Assumptions

Let $\mathbf{D}_{ijt} = (Y_{ijt}, Y_{jit})'$ be the dyad referred to units i and j for time window t , with $i, j = 1, \dots, n$, $i < j$, and $t = 1, \dots, T$, where T is the number of time intervals (windows) that span all the period of observation. In particular, every Y_{ijt} is a binary variable equal to 1 if there is at least one relation in the time window t with i being the sender and j the receiver. Let y_{ijt} denote a realization of Y_{ijt} and use a similar convention based on small letters for all other random variables and vectors.

The first assumption of our model is that, given latent effects corresponding to the general tendency to connect with other units, all vectors \mathbf{D}_{ijt} are conditionally independent. Moreover, we assume that:

$$p(\mathbf{D}_{ijt} = \mathbf{d}_{ijt} | \alpha_i, \alpha_j, \beta_i, \beta_j, \gamma_i, \gamma_j, \mu_t, \rho_t) = \frac{\exp[y_{ijt}(\mu_t + \alpha_i + \beta_j) + y_{jit}(\mu_t + \alpha_j + \beta_i) + y_{ijt}y_{jit}(\rho_t + \gamma_i + \gamma_j)]}{K(\alpha_i, \alpha_j, \beta_i, \beta_j, \gamma_i, \gamma_j, \mu_t, \rho_t)}, \quad (3.1)$$

where μ_t and ρ_t are, respectively, the general connectedness and reciprocity parameters referred to the time window t . Moreover, α_i is the specific tendency of unit i to be a sender, β_i is the specific tendency to be a receiver, and γ_i is the tendency of the same unit to reciprocate; $K(\alpha_i, \alpha_j, \beta_i, \beta_j, \gamma_i, \gamma_j)$ is the normalizing constant. To ensure model identifiability, all these individual parameters are constrained to have a mean equal to zero, which is equivalent to requiring that

$$\sum_{i=1}^n \alpha_i = \sum_{i=1}^n \beta_i = \sum_{i=1}^n \gamma_i = 0, \quad (3.2)$$

so that they can be interpreted as deviances from the general means. In order to adopt a more compact notation, we introduce $\phi_i = (\alpha_i, \beta_i, \gamma_i)'$, so that the probability in (3.1) is also indifferently denoted by $p(\mathbf{D}_{ijt} = \mathbf{d}_{ijt} | \phi_i, \phi_j, \mu_t, \rho_t)$ and the same applies with other probabilities and related objects.

Regarding the interpretation of the different effects, it is worth noting that the relation from unit i to unit j is decomposed as follows:

$$\log \frac{p(Y_{ijt} = 1 | \phi_i, \phi_j, Y_{jit} = 0)}{p(Y_{ijt} = 0 | \phi_i, \phi_j, Y_{jit} = 0)} = \mu_t + \alpha_i + \beta_j.$$

Moreover, considering the log-odds ratio for the dyad – a very well-known measure of association between binary variables – we have:

$$\log \frac{p(Y_{ijt} = 0, Y_{jit} = 0 | \phi_i, \phi_j) p(Y_{ijt} = 1, Y_{jit} = 1 | \phi_i, \phi_j)}{p(Y_{ijt} = 0, Y_{jit} = 1 | \phi_i, \phi_j) p(Y_{ijt} = 1, Y_{jit} = 0 | \phi_i, \phi_j)} = \rho_t + \gamma_i + \gamma_j.$$

Therefore, $\rho_t + \gamma_i + \gamma_j = 0$ implies conditional independence between the variables in each dyad, whereas $\rho_t + \gamma_i + \gamma_j > 0$ implies positive association between these variables. In terms of social behavior, the latter condition means that there is a tendency to reciprocate relations in the same

time window: the conditional probability that one of the variables in the dyad is equal to 1 increases when the other variable is equal to 1 with respect to 0.

Two crucial points are the modeling assumptions on the effects α_i , β_i , and γ_i , $i = 1, \dots, n$, and on the trajectories μ_t and ρ_t , $t = 1, \dots, T$. Regarding the first aspect, the choice is between a random-effects approach – in which suitable distributions are assumed for these effects – and a fixed-effects approach – in which they are seen as fixed parameters or are modeled on the basis of fixed parameters. We adopt the second approach for multiple reasons. First, it guarantees a high degree of flexibility paired with a stable and reliable estimation of effects. Second, the use of a fixed-effects approach is related to the nature of the problem at hand and to the relevant amount of information available due to the longitudinal structure of the data. Regarding the trajectories, in principle, we could assume a completely free structure based on time dummies. However, in order to obtain more interpretable and stable results, we could use a more constrained structure based on a polynomial of suitable order or, as a compromise, parametrize μ_t and ρ_t on the basis of splines of appropriate order – typically the third – and with knots suitably chosen. These parametrizations may be expressed, in general, as follows:

$$\mu_t = [\mathbf{z}_t^{(1)}]' \boldsymbol{\nu}, \quad (3.3)$$

$$\rho_t = [\mathbf{z}_t^{(2)}]' \boldsymbol{\tau}, \quad (3.4)$$

where $\mathbf{z}_t^{(1)}$ and $\mathbf{z}_t^{(2)}$ are design vectors to be defined appropriately. For instance, using time dummies, we have that $\mathbf{z}_t^{(1)}$ is a column vector of T zeros apart from the t -th element that is equal to one, and $\mathbf{z}_t^{(2)}$ is defined in the same way. Using polynomials of order 3, we have $\mathbf{z}_t^{(1)} = \mathbf{z}_t^{(2)} = (1, t, t^2, t^3)'$. Using the splines, these vectors have a more complex structure, which, however, can be easily defined based on well-known routines. In particular, we use the function *bs* from the R package *splines* (Chambers, Hastie, et al., 1992).

3.2.2 Maximum composite likelihood estimation

Estimation is based on the maximization of the pairwise log-likelihood function

$$\begin{aligned} p\ell(\boldsymbol{\Phi}, \boldsymbol{\psi}) &= \sum_{i=1}^{n-1} \sum_{j=i+1}^n \ell_{ij}(\phi_i, \phi_j, \boldsymbol{\psi}), \\ \ell_{ij}(\phi_i, \phi_j, \boldsymbol{\psi}) &= \sum_{t=1}^T \log p(\mathbf{D}_{ijt} = \mathbf{d}_{ijt} | \phi_i, \phi_j, \boldsymbol{\psi}), \end{aligned} \quad (3.5)$$

with $\boldsymbol{\Phi}$ being a matrix obtained by casting vectors ϕ_i , $i = 1, \dots, n$, and $\boldsymbol{\psi} = (\boldsymbol{\nu}', \boldsymbol{\tau}')'$. It is convenient to reformulate the previous functions using matrix notation. To this aim, let

$$\mathbf{w}_{ijt} = \begin{pmatrix} I(y_{ijt} = 0, y_{jit} = 0) \\ I(y_{ijt} = 0, y_{jit} = 1) \\ I(y_{ijt} = 1, y_{jit} = 0) \\ I(y_{ijt} = 1, y_{jit} = 1) \end{pmatrix}, \quad \mathbf{p}_{ijt} = \begin{pmatrix} p(\mathbf{d}_{ijt} = (0, 0)') \\ p(\mathbf{d}_{ijt} = (0, 1)') \\ p(\mathbf{d}_{ijt} = (1, 0)') \\ p(\mathbf{d}_{ijt} = (1, 1)') \end{pmatrix}.$$

Vector \mathbf{w}_{ijt} contains an indicator function taking value one for the realized trading configurations between sender i and receiver j at time t , and zero otherwise. Vector \mathbf{p}_{ijt} contains, for each pair of actors, the probability of being involved in four distinct types of dyadic exchange. Given two

social actors i and j , we refer to the following cases. First, the probability of observing a transaction in which neither i nor j is involved as a sender or receiver. Second, the probability of i not being involved in a dyadic transaction as a sender and j being involved as a receiver. Third, the same as before but with i and j swapped in their roles of senders and receivers. Fourth, the probability of both i and j being involved in a dyadic transaction as the sender and the receiver of a tie.

Note that

$$\mathbf{p}_{ijt} = \frac{1}{\mathbf{1}' \exp(\mathbf{X}_t^{(1)} \phi_i + \mathbf{X}_t^{(2)} \phi_j + \mathbf{Z}_t \psi)} \exp(\mathbf{X}_t^{(1)} \phi_i + \mathbf{X}_t^{(2)} \phi_j + \mathbf{Z}_t \psi),$$

for design matrices $\mathbf{X}_{it}^{(1)}$, $\mathbf{X}_{jt}^{(2)}$, and \mathbf{Z}_t defined as:

$$\mathbf{X}_t^{(1)} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \\ 1 & 1 & 1 \end{pmatrix}, \quad \mathbf{X}_t^{(2)} = \begin{pmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 1 & 1 \end{pmatrix}, \quad \mathbf{Z}_t = \begin{pmatrix} \mathbf{0} & \mathbf{0} \\ [\mathbf{z}_t^{(1)}]' & \mathbf{0} \\ [\mathbf{z}_t^{(1)}]' & \mathbf{0} \\ 2[\mathbf{z}_t^{(1)}]' & [\mathbf{z}_t^{(2)}] \end{pmatrix}.$$

Consequently, we can write

$$\ell_{ij}(\phi_i, \phi_j, \psi) = \sum_{t=1}^T \mathbf{w}_{ijt}' \log \mathbf{p}_{ijt}.$$

In order to numerically estimate the model by maximum likelihood, we need to compute the derivatives of the pairwise log-likelihood with respect to the parameters. These derivatives are as follows:

$$\begin{aligned} \frac{\partial p\ell(\Phi, \psi)}{\partial \phi_i} &= \sum_{\substack{j=1 \\ j \neq i}}^n \sum_{t=1}^T [\mathbf{X}_t^{(1)}]' (\mathbf{w}_{ijt} - \mathbf{p}_{ijt}), \\ \frac{\partial p\ell(\Phi, \psi)}{\partial \psi} &= \sum_{i=1}^{n-1} \sum_{j=i+1}^n \sum_{t=1}^T \mathbf{Z}_t' (\mathbf{w}_{ijt} - \mathbf{p}_{ijt}). \end{aligned}$$

The second derivatives are:

$$\begin{aligned} \frac{\partial^2 p\ell(\Phi, \psi)}{\partial \phi_i \partial \phi_i'} &= \sum_{\substack{j=1 \\ j \neq i}}^n \sum_{t=1}^T [\mathbf{X}_t^{(1)}]' \mathbf{\Omega}_{ijt} \mathbf{X}_{ijt}^{(1)}, \\ \frac{\partial^2 p\ell(\Phi, \psi)}{\partial \psi \partial \psi'} &= \sum_{i=1}^{n-1} \sum_{j=i+1}^n \sum_{t=1}^T \mathbf{Z}_t' \mathbf{\Omega}_{ijt} \mathbf{Z}_t, \end{aligned}$$

with $\mathbf{\Omega}_{ijt} = \text{diag}(\mathbf{p}_{ijt}) - \mathbf{p}_{ijt} \mathbf{p}_{ijt}'$.

The estimation algorithm is based on starting from initial parameter values, which are iteratively updated. Denote with $\phi_i^{(h)}$ and $\psi^{(h)}$ the corresponding parameters returned at the end of h -th step of the algorithm, and with $\Phi^{(h,i)}$ the matrix obtained by stacking $\phi_1^{(h+1)}, \dots, \phi_{i-1}^{(h+1)}$ and $\phi_i^{(h)}, \dots, \phi_n^{(h)}$. We first update the individual parameters as

$$\phi_i^{(h)} = \phi_i^{(h-1)} + \left[\frac{\partial^2 p\ell(\Phi^{(h-1,i)}, \psi^{(h-1)})}{\partial \phi_i \partial \phi_i'} \right]^{-1} \frac{\partial p\ell(\Phi^{(h-1,i)}, \psi^{(h-1)})}{\partial \phi_i}, \quad i = 1, \dots, n,$$

and the parameters in Φ are then centered so that the constraint in (3.2) is fulfilled. Note that the first and second derivatives used in the previous updates can be quickly computed as the derivatives of

$$\sum_{j \neq i} \ell_{ij}(\phi_i, \phi_j, \psi), \quad (3.6)$$

avoiding considering all data that are not referred to unit i , as shown above.

Then, the global parameters are updated as:

$$\psi^{(h)} = \psi^{(h-1)} + \left[\frac{\partial^2 p\ell(\Phi^{(h)}, \psi^{(h-1)})}{\partial \psi \partial \psi'} \right]^{-1} \frac{\partial p\ell(\Phi^{(h)}, \psi^{(h-1)})}{\partial \psi}.$$

The steps are iterated until convergence, which is checked on the basis of the rule

$$\frac{p\ell(\Phi^{(h)}, \psi^{(h)}) - p\ell(\Phi^{(h-1)}, \psi^{(h-1)})}{\left| p\ell(\Phi^{(h-1)}, \psi^{(h-1)}) \right|} \leq \varepsilon$$

where ε is a suitable tolerance level such as 10^{-10} .

To make inference on the parameters of interest, namely those in (3.3) and (3.4), we adopt a parametric bootstrap procedure in which, say, 250 datasets are simulated from the estimated model (Efron and Tibshirani, 1986, 1997). Note that, thanks to the model assumptions, this resampling scheme may be simply implemented so as to obtain standard errors and confidence intervals for the parameters of interest.

A final, yet crucial, point is that of model selection. In fact, as we have already explained, distinct models are possible using different specifications of the design vectors in (3.3) and (3.4) for μ_t and ρ_t . To this aim, we rely on a cross-validation procedure, taking inspiration from Smyth (2000). In particular, at each iteration of the procedure, we define the *training* dataset by randomly removing half of the observations in the data vectors \mathbf{w}_{ijt} . The removed observations give rise to the *validation* dataset. For each training dataset, parameter estimates are computed by maximizing a version of $p\ell(\Phi, \psi)$, which is defined as in (3.6) with reference to the selected observations only. The corresponding goodness-of-fit on the validation dataset is measured on the basis of the same expression defined in (3.6), obtaining, in this way, the cross-validated composite log-likelihood. Finally, at the end of the procedure, we compute, for each model specification, the average of these functions, and the model with the highest average value is then chosen. This approach has been successfully experimented with by Bartolucci et al. (2017) in a different empirical setting, where a composite likelihood method related to the one adopted in this paper is used.

3.3 Empirical setting, data, and network construction

We situate our study within the context of the European interbank market, a funding market where banks extend loans of varying maturities to one another to meet both their liquidity needs and the reserve requirements imposed by the ECB, with the aim of preventing short-term liquidity shocks. Studying the links that banks establish by channeling liquidity from institutions with surplus funds to those in deficit is crucial for promoting proper liquidity management programs and ultimately ensuring financial stability. Our modeling approach examines these links by considering the differences

in activity levels between members of an ad hoc pair of selected banks and by tracking the temporal evolution of their connectivity structure.

In line with recent studies describing the network structure of the European interbank market (Finger et al., 2013; Fricke and Lux, 2015; Finger and Lux, 2017; Hatzopoulos et al., 2015; Iori et al., 2015), we restrict our attention to the interbank relations as registered in the overnight segment. Overnight contracts require borrowers to pay the funds back by the beginning of the following business day, and represent approximately 90% of the global amount of loan contracts. Their analysis is of primary relevance to understand the dynamics of the European interbank market (Beaupain and Durré, 2008). First, it is expected to impact the entire market dynamics by adjusting the liquidity positions of credit institutions within a very short time frame. Second, the evolution of overnight interest rates is strongly influenced by the regular refinancing operations encouraged by the ECB. Third, in short-term loans, utilitarian motivations to trade prevail over speculative ones, thus reinforcing the relationships among credit institutions.

We collected data on interbank credit relations from January 2006 to December 2015 on the e-MID trading platform – the most accurate data source for interbank loans (Beaupain and Durré, 2011). The e-MID trading platform is a quote-driven market that makes quotes public in terms of the exchanged amount, offered interest rate, and involved counterparties. Traders are identified by their unique ID number, an alphanumeric code displaying the country of origin and a four-digit label. Transactions taking place on the e-MID platform are collected in time-stamped datasets where each line corresponds to a credit contract.

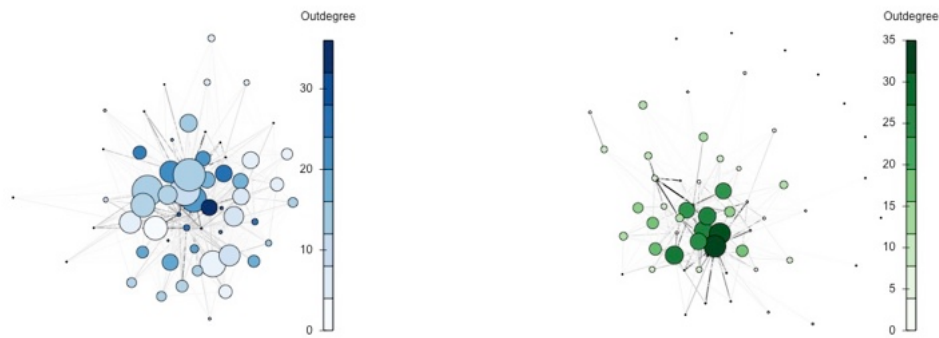
In our empirical application, we transform the time-ordered sequence of lending events into directed adjacency matrices. Lenders and borrowers of liquidity are listed along the rows and the columns, respectively. The cells indicate if credit has been extended by the bank registered in the row to the bank listed in the column. In the cell corresponding to sender i and receiver j , we find one if a loan has been extended from i to j , and zero otherwise. The elements along the diagonal of this matrix are assumed to be equal to zero since a bank cannot trade with itself. To observe empirical regularities and obtain a homogeneous sample of banks in terms of their activity, we followed Finger et al. (2013) and aggregated our data on a quarterly basis, resulting in a set of $T = 40$ windows of network observations. The output of our data treatment is an array composed of 40 matrices whose dimension is 59×59 – which is the number of banks that have been active in each year between January 2006 and December 2015 by entering into 228,817 liquidity contracts overall. Out of the 59 banks, the only bank that was used to act exclusively as a liquidity provider has been removed from the sample. This is because logit models with fixed effects do not allow for the treatment of entries that are structurally composed of zeros. Table 3.1 shows some basic descriptive statistics of our quarterly networks that make sense of the exchange volume during the observation period.

Tab. 3.1: Main descriptive network statistics computed by aggregating raw data in $T = 40$ windows of network observations.

# transactions	228,817
# edges	2,295
# vertices	58
Density	0.69
Reciprocity	0.78

A single observation represents the network of quarterly-aggregated lending relationships among the $n = 58$ banks active in all years. In detail, the resulting sample comprises 57 Italian banks and only

one foreign credit institution. Such a result is not surprising considering that the e-MID trading platform is based in Milan and the Italian banking system is very fragmented. Nevertheless, the disproportionate percentage of Italian banks has not prevented the e-MID market from replicating the trading dynamics of the European interbank market (Beaupain and Durré, 2008). If we focused on the number of banks active in each quarter, we would have a network composed of only 13 banks – a sample too small to properly represent the lending behavior of the entire European market. From a statistical perspective, quarterly-based aggregation is optimal in the sense that most network statistics have been proved to become stable around the quarterly basis (Finger et al., 2013). Accordingly, networks based on that time window are more likely to provide an exhaustive representation of preferential lending relationships, simply by revealing the majority of existing links. Figure 3.1 shows two distinct snapshots of the interbank credit network. Figure 3.1a refers to the first wave of network observations, that is, the first quarter of 2006, while Figure 3.1b refers to the last quarter of 2015, corresponding to the end of our sample. Nodes' color intensity and size are proportional to the number of outgoing and ingoing ties, respectively. Both Figures 3.1a and 3.1b indicate that usually active lenders are also active borrowers, thus signaling the presence of key players with fluid market roles. This tendency clearly emerges from Figure 3.1b, where the darkest nodes are also the biggest ones. However, at the beginning of our observation period, such a tendency is less strong. On one hand, Figure 3.1a shows that there are some banks that mostly act as liquidity providers and borrowers. On the other hand, it displays a relatively large proportion of actors whose trading activity is characterized by fluid market roles. From an economic viewpoint, this fact is of great relevance. In markets with no preassigned roles, sellers account for the trading behavior of their current buyers when selecting new partners. In particular, sellers seem to choose their new buyers within the subset of actors to which their buyers have already sold, thus reinforcing those market actors' mutual dependencies that, in turn, may enable claims of resources (Uzzi, 1996) and, eventually, affect price determination (Baker, 1984).



(a) Interbank credit network in 2006Q1

(b) Interbank credit network in 2015Q4

Fig. 3.1: Interbank credit relations at the beginning (2006Q1) and at the end (2015Q4) of the observation period. Nodes' color intensity and size reflect the number of outgoing and ingoing ties, respectively.

3.4 Results

Our model allows for the simultaneous estimation of parameters that measure the overall market tendency to connectivity (μ_t) and reciprocity (ρ_t) over time, and parameters that measure, with

respect to the average market trend, the individual propensity of each bank to act as a liquidity lender (α_i), borrower (β_i), and to reciprocate transactions (γ_i and γ_j). Therefore, we can show how each lender is linked to the market, that is, how it relates to the collection of all its possible trading counterparts, and, at a lower level, how each lender is related to a specific trading partner. Moreover, lending and borrowing behaviors associated with a specific pair of market actors can be analyzed in their time evolution.

We have estimated four distinct models on quarterly transactions as they occurred on the e-MID trading platform from January 2006 to December 2015. The models are ordered from the smallest (most constrained with fewest parameters) to the largest (most flexible with the largest parameter space), each one based on a different specification of the design vectors in (3.3) and (3.4). Model 1 refers to polynomial latent trajectories of order 3. Model 2 is based on spline trajectories of the same order, with three knots at 2007Q3, 2008Q4, and 2010Q2, to distinguish phases based on exogenous shocks that severely hit financial markets. A period of turmoil began on August 9, 2007 (2007Q3), when BNP Paribas, the largest listed bank in France, froze some of its funds, citing problems in the US subprime mortgage sector. The collapse of Lehman Brothers' on September 15, 2008 (2008Q4) determined the beginning of the Global Financial Crisis, which eventually ended up in a sovereign debt crisis occurred in May 2010 when the 10-years yield spread between Greek and German government bonds reached – at the time – the historical high of about 1,000 basis points (Drudi et al., 2012). Building on Model 2, Model 3 features annual knots at each first quarter, starting from 2007Q1, to capture changes in the interbank market at a finer-grained timescale. Finally, Model 4 includes time-fixed effects through dummy variables in each quarter, making it the most flexible model.

3.4.1 Selected model

The cross-validation procedure based on composite likelihood and described at the end of Section 3.2 suggests that Model 3 is the most appropriate to describe the temporal evolution of market levels of connectedness, reciprocity, and individual actors' attractiveness as buyers and sellers of liquidity. With a cross-validated composite log-likelihood equal to -25,947.42, the model based on annual knots of the spline is preferred to Model 4 (-25,961.60), Model 2 (-26,022.22), and Model 1 (-26,087.15). Empirical results and descriptive analysis fully support this. Therefore, in the sequel, we detail results for Model 3 and give hints to the distinguished features of the alternative models at the end of the section.

The introduction of spline knots at convenient time points allows to capture the effects of macro-events and exogenous shocks ultimately associated with those time points. The choice of spline knots in Model 3 has been guided by a collection of studies promoted by the ECB itself with the general aim of guaranteeing the sustainability of the monetary union of the euro area (Angelini et al., 2011; Beaupain and Durré, 2008, 2011; Drudi et al., 2012). The idea of introducing knots on each first quarter, from 2007 on, is motivated by the need of keeping track of short-term effects produced by major changes in the European interbank market during the observation period – namely the financial turmoil (August 9, 2007 to September 14, 2008), the Global Financial Crisis (September 15, 2008 to May 7, 2010) and the euro area sovereign debt crisis (started on 8 May 2010 and not yet ended for some countries of the European Union).

To make sense of splines coefficients, we report in Table 3.2 the point estimates, the 95% bootstrapped confidence intervals, and the standard errors for ν and τ – used to parametrize the temporal effects μ_t and ρ_t , respectively. Table 3.3 completes the analysis by reporting some descriptive statistics corresponding to individual parameters α_i , β_i , and γ_i .

Tab. 3.2: Point estimates, 95% bootstrapped confidence intervals, and standard errors for ν and τ

	ν	95% CI	s.e.	τ	95% CI	s.e.
1	-1.92	[-2.03, -1.82]	0.06	0.70	[0.32, 0.94]	0.16
t	-1.63	[-1.80, -1.47]	0.09	0.35	[-0.13, 0.74]	0.23
t^2	-1.90	[-2.09, -1.73]	0.09	1.03	[0.58, 1.37]	0.20
t^3	-0.84	[-1.00, -0.71]	0.07	-0.14	[-0.60, 0.18]	0.20
k_{2007Q1}	-2.24	[-2.38, -2.10]	0.07	0.25	[-0.20, 0.55]	0.20
k_{2008Q1}	-1.84	[-2.00, -1.71]	0.07	-0.07	[-0.64, 0.26]	0.21
k_{2009Q1}	-1.69	[-1.81, -1.57]	0.06	0.41	[0.02, 0.78]	0.19
k_{2010Q1}	-2.19	[-2.32, -2.08]	0.06	0.30	[-0.10, 0.63]	0.21
k_{2011Q1}	-2.51	[-2.64, -2.40]	0.07	0.55	[0.08, 0.95]	0.23
k_{2012Q1}	-2.20	[-2.36, -2.06]	0.08	0.05	[-0.51, 0.51]	0.25
k_{2013Q1}	-2.17	[-2.38, -1.99]	0.10	1.05	[0.48, 1.57]	0.29
k_{2014Q1}	-3.17	[-3.38, -3.00]	0.10	-0.04	[-0.82, 0.64]	0.38
k_{2015Q1}	-3.01	[-3.16, -2.89]	0.07	0.00	[-0.98, 0.53]	0.37

Both the global parameters μ_t and ρ_t reveal that market levels of connectedness and reciprocity change substantially over the whole observational period. In particular, the sharply decreasing curve associated with μ_t (Figure 3.2) shows that the trading activity on the European interbank market strictly depends on the economic outlook. When economic activities are flourishing – as it was at the beginning of the observational period – banks are prone to lend and borrow money to each other in order to sustain their daily investment needs. In the presence of sluggish growth and falling productivity – as it happened during the Global Financial Crisis – banks usually do not need to ask for extra money to accomplish their regular activities.

On the contrary, the propensity to engage in reciprocal exchange ρ_t reveals a more stable trend (Figure 3.3). Our model captures two stylized facts related to the development of the interbank market during the progressive emergence of the Global Financial Crisis: (i) the decrease in reciprocated transactions after the turmoil period (2007Q3). Alongside the general decrease in trading activities, it signals that, in periods of market turbulence, banks typically reduce their activity and focus on their role as liquidity providers, primarily with a select group of trading counterparts. The rationale behind their behavior is to manage the risk associated with the deteriorating creditworthiness of some credit institutions; (ii) the progressive increase in reciprocated transactions after 2010. Alongside a temporal increase in transactions, this highlights the effectiveness of the intervention measures promoted by the ECB, aimed at addressing the loss of confidence and the malfunctioning of various financial market segments.

Tab. 3.3: Descriptive statistics for the estimates of parameters α_i , β_i , and γ_i

	α_i	β_i	γ_i
min	-3.04	-4.17	-1.22
max	1.82	2.77	2.80
mean	0.00	0.00	0.00
sd	1.04	1.75	0.74
1st quartile	-0.37	-0.90	-0.44
median	0.16	0.25	-0.21
3rd quartile	0.72	1.27	0.47

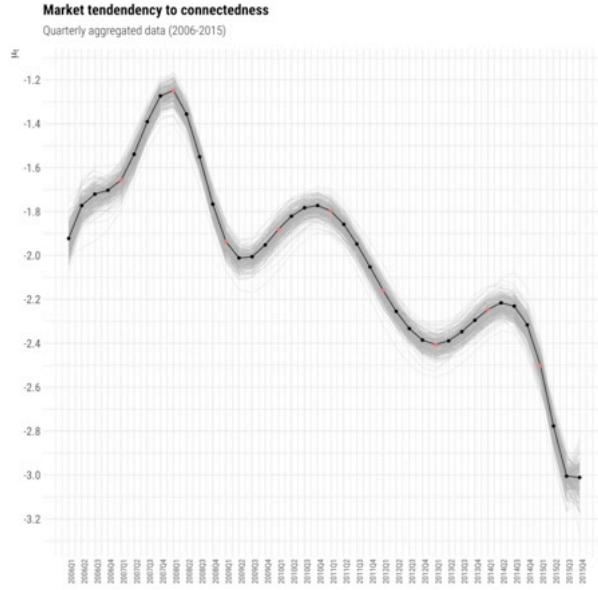


Fig. 3.2: Market tendency to connectedness (μ_t). Gray lines represent 250 bootstrapped trajectories.

The claims above are also supported by some descriptive statistics. On one hand, the number of transactions per quarter (Figure 3.4a), whose shape roughly resembles that of μ_t , clearly reveals the market seized up as a consequence of the Global Financial Crisis development. On the other hand, the percentage of reciprocated transactions per quarter (Figure 3.4b), whose shape resembles well that of ρ_t , shows the accuracy of model estimates.

Empirical evidence in favor of reciprocity as being strictly related to individual banks' attractiveness as buyers and sellers is provided by Figure 3.5, showing the correlation matrix between attractiveness parameters α_i , β_i , and γ_i . The histograms on the diagonal of Figure 3.5 reveal insights on role specialization. The histogram of the α_i distribution is skewed to the left, indicating that a small number of banks exhibit a strong preference for being liquidity providers compared to the market average. The histogram related to the β_i is less skewed than the previous one, indicating that most banks prefer to trade on the e-MID platform as liquidity borrowers. Finally, the histogram referring to γ_i reveals that banks are not particularly prone to reciprocate previous transactions. However, a small sample of banks is very active on the interbank market on both sides of the market interface. The substantive absence of correlation between α and β ($s.e. = 0.02$) and its negative sign support what emerges from the corresponding histograms: the e-MID market is particularly attractive for collecting liquidity. The negative correlations between the α_i and γ_i ($s.e. = 0.10$) and between the β_i and γ_i ($s.e. = 0.11$) reveal that the more banks stick to a specific market role, the less they tend to be involved in reciprocity.

Our model also enables the analysis of distinct patterns of exchange involving a specific pair of selected banks. To illustrate this, we consider the most balanced pair of buyers and sellers in terms of the number of reciprocated transactions—that is, the pair whose members essentially act as mutual liquidity providers and borrowers, with a negligible difference between their outgoing and incoming liquidity flows. As an example, we analyze the trading activity that occurred between banks $i = 47$ (IT0258) and $j = 52$ (IT0265), with bank i acting as a liquidity provider (sender) and bank j acting as a liquidity borrower (receiver). This pair of actors extended overnight loans to each other 103 and 100 times, respectively, during the observation period.

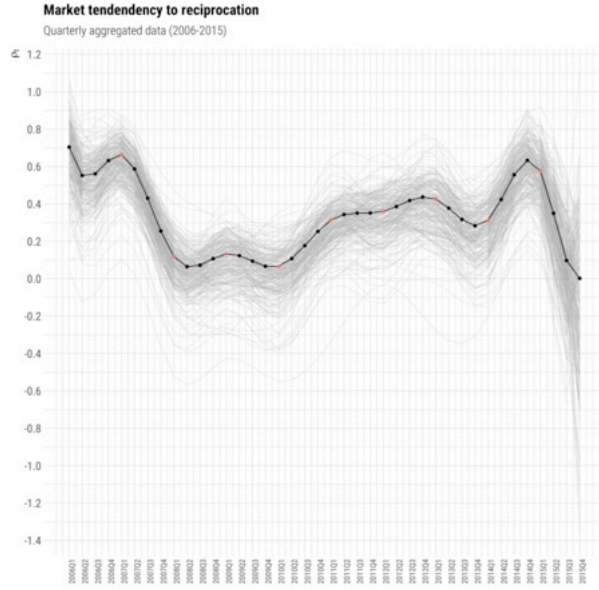


Fig. 3.3: Market tendency to reciprocity (ρ_t). Gray lines represent 250 bootstrapped trajectories.

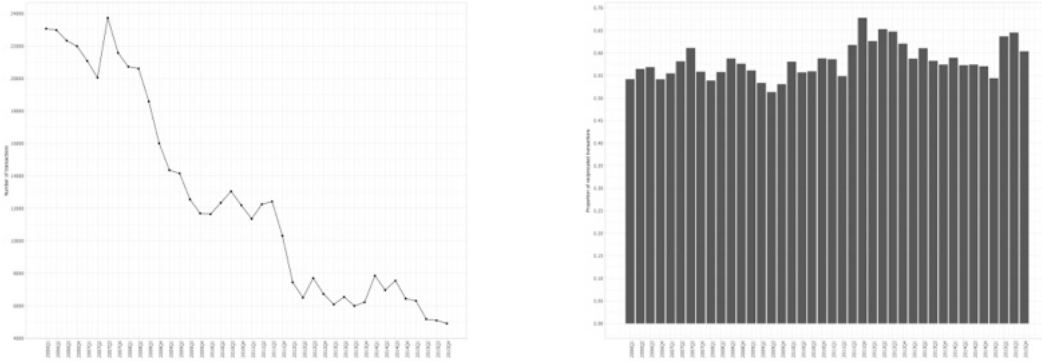


Fig. 3.4: Number of transactions and percentage of reciprocated transactions per quarter.

Figure 3.6 shows, for each quarter, the estimated probability of having banks IT0258 and IT0265 involved in a trading instance as lender and borrower, respectively. We call this probability p_{ijt} with $p_{ijt} = p(\mathbf{D}_{ijt} = (1,1)' | \phi_i, \phi_j)$ and in gray we indicate the corresponding 95% bootstrapped confidence interval. We observe that the probability p_{ijt} increases sharply until the beginning of the turmoil period in 2007Q3 and then remarkably decreases for almost a year after the onset of the Global Financial Crisis. Despite isolated signs of recovery, the curve shape after 2008Q4 totally reflects the contraction of traded volumes. To address the uncertainty generated by the market seizing up, some banks began adopting a micro-prudential trading policy due to concerns about future liquidity needs and potential non-repayment of pending loans. Their peers, in turn, responded to their liquidity hoarding by adopting the same behavior (Acharya and Skeie, 2011; Berrospide, 2012). Furthermore, since 2012, the progressive stabilization of probabilities associated with i and j being trading partners reflects the positive effects of the quick adoption of a renovated regulatory system. While precautionary considerations continue to impact the interbank market, the adoption of new rules has enhanced the robustness of the system and the creditworthiness of its counterparties.

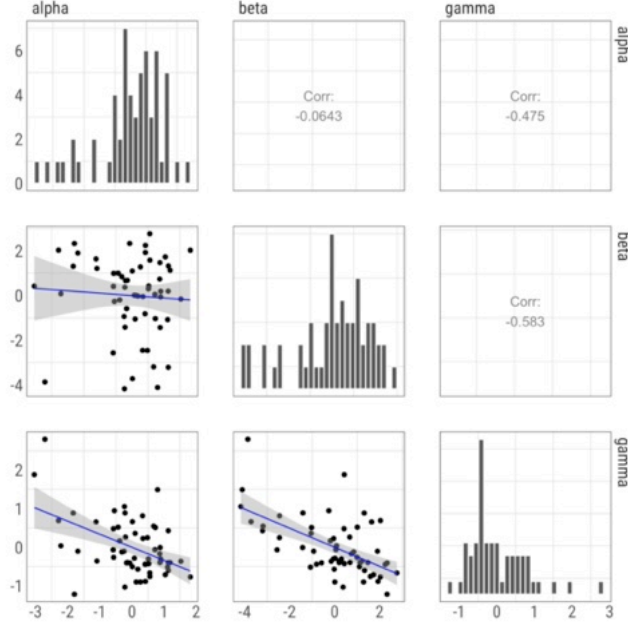


Fig. 3.5: Correlation between attractiveness parameters α_i , β_i , and γ_i . Blue lines correspond to linear trends, while gray bands are the 95% confidence intervals.

Each of the two actors included in the pair can also be examined individually. Accordingly, the probabilities of being linked to the market as liquidity providers or borrowers are computed. Figure 3.7, for example, displays the propensity of actor IT0258 to initiate and attract a transaction as liquidity provider ($p_{i \cdot t}$) and borrower ($p_{\cdot it}$), respectively. More precisely, we have

$$p_{i \cdot t} = \frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^n [p(\mathbf{D}_{ijt} = (1, 0)' | \Phi) + p(\mathbf{D}_{ijt} = (1, 1)' | \Phi)],$$

$$p_{\cdot it} = \frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^n [p(\mathbf{D}_{ijt} = (0, 1)' | \Phi) + p(\mathbf{D}_{ijt} = (1, 1)' | \Phi)].$$

We will generally refer to $p_{i \cdot t}$ and $p_{\cdot it}$ as the probability or propensity of subject i to, respectively, lend or borrow liquidity.

Generally, actor IT0258 exhibits a greater propensity to lend liquidity. Its activity on the market in both directions decreases over time. However, its lending propensity decreases more sharply than its borrowing attitude. This might be due to the perceived counterpart risk, which was amplified after the turmoil in 2007Q3 and the general contraction of the interbank market. Moreover, the moderate expansion and contraction of both lending and borrowing activities observed after 2008Q4 may reflect the implications of short-term policies adopted by the ECB in response to both the money market collapse and the dismal economic outlook. For example, many major central banks in Europe and around the world introduced both standard measures in the form of interest rate cuts and non-standard measures in the form of large-scale short-term and longer-term refinancing operations (Drudi et al., 2012).

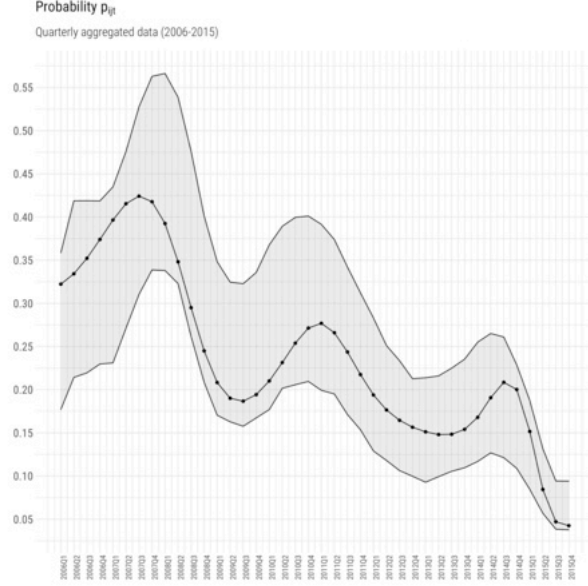


Fig. 3.6: Probability of interaction between sender bank IT0258 and receiver bank IT0265. The gray band refers to a 95% bootstrapped confidence interval.

Given bank IT0258 as a liquidity provider, for each quarter and each of its trading counterparts, we can calculate the number of reciprocated trading sequences in which it is involved. In this regard, an example is provided by Figure 3.8 that shows the strength of reciprocity between bank IT0258 and each of its trading counterparts at the beginning (2006Q1) and the end (2015Q4) of the observation period. We can easily observe that in both temporal snapshots, actor IT0258 establishes close, reciprocated relationships with very few trading partners. Its activity increases over time, and the composition of its partner's portfolio changes accordingly.

Finally, by keeping the focus on actor IT0258, our model enables us to compute the probability that bank IT0258 will be both a liquidity seller and buyer. In so doing, we combined the estimated probabilities of acting as both a liquidity provider and borrower in the presence and absence of reciprocity. In this respect, Figure 3.9 displays the probability of bank IT0258 being involved in the four different trading configurations mentioned in Section 3.2.2 and the corresponding 95% bootstrapped confidence intervals.

By considering i as a generic sender and j as the panel of potential receivers, p_{i10t} indicates the probability of acting as a liquidity sender only, while p_{i11t} refers to the probability of being involved in a reciprocity of liquidity. In a similar fashion, p_{i01t} represents the probability of acting as a liquidity receiver only, while p_{i00t} shows the probability of not being selected as a trading counterpart by any sender or receiver. These probabilities are defined in general as

$$p_{iklt} = \frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^n p(\mathbf{D}_{ijt} = (k, l)' | \Phi), \quad k, l = 0, 1.$$

Figure 3.9 shows that bank IT0258 mostly acts as a liquidity provider, as proved by the light blue line p_{i10t} being always above the green one (p_{i01t}). However, its activity as a liquidity seller is more volatile than its borrowing activity, as the different widths of the confidence bands show. This trading trend is

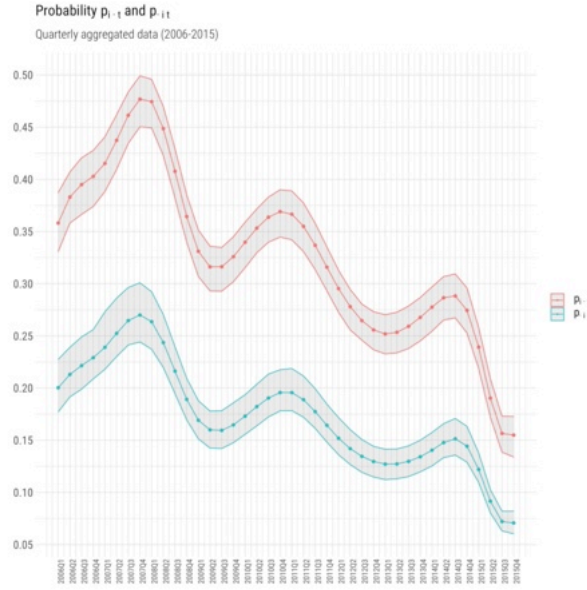


Fig. 3.7: Probability of bank $i = \text{IT0258}$ being a provider and borrower of liquidity. In red, we indicate the probability of bank $i = \text{IT0258}$ being a liquidity provider. In light blue, we indicate the probability of bank $i = \text{IT0258}$ being a liquidity borrower. Gray bands represent 95% bootstrapped confidence intervals.

not surprising, considering that counterpart creditworthiness began to decline even after the interbank market freeze in 2007Q3. The corresponding reduction in trading activity is clearly captured by the red line p_{i00t} , which starts increasing from 2008Q4. The difficulties faced by the European interbank market after the emergence of the Global Financial Crisis are well represented in the flowing patterns of light blue (p_{i10t}), green (p_{i01t}), and purple (p_{i11t}) lines. When considering the line associated with the probability of being engaged in reciprocated transactions p_{i11t} , we notice that it is at the bottom of the plot and below all the other lines. It means that bank IT0258 entertains balanced exchange relations with a restricted panel of trading partners, whose composition is reasonably kept almost invariant along the whole observation period. The economic rationality sustaining this trading behavior might be the need to perpetuate relationships only with trusted counterparts in order to minimize credit risk and ultimately prevent money losses.

The level of activity of bank IT0258 – described by the four distinct profiles of exchange in Figure 3.9 – can be loosely related to the global parameter μ_t . The shape of μ_t in Figure 3.2 resembles the functional shape of p_{i10t} and p_{i01t} in Figure 3.9, thus confirming that the dyad composed of the liquidity provider IT0258 and the liquidity borrower IT0265 is a good one to depict, at a micro-level, the dynamics of the whole interbank market. By following the same line of reasoning and narrowing the focus on reciprocity, the level of bank IT0258 reciprocated activity – as measured by p_{i11t} in Figure 3.9 – can be compared to ρ_t . The shape of ρ_t , as it emerges from Figure 3.3, resembles the functional shape of p_{i11t} in Figure 3.9, thus showing that the dyad composed of IT0258 and IT0265 is representative of the temporal evolution of reciprocity. Moreover, when parameter ρ_t is paired to Figure 3.8, the shape of ρ_t curve might signal that trading relationships based on reciprocity take time to build but, once established, are usually maintained over time and work as an insurance against counterpart risk, especially when economic and business cycles are volatile. On a finer-grained level, the general idea of reciprocity as a promoter of trust and cohesion is supported by Figure 3.8, showing

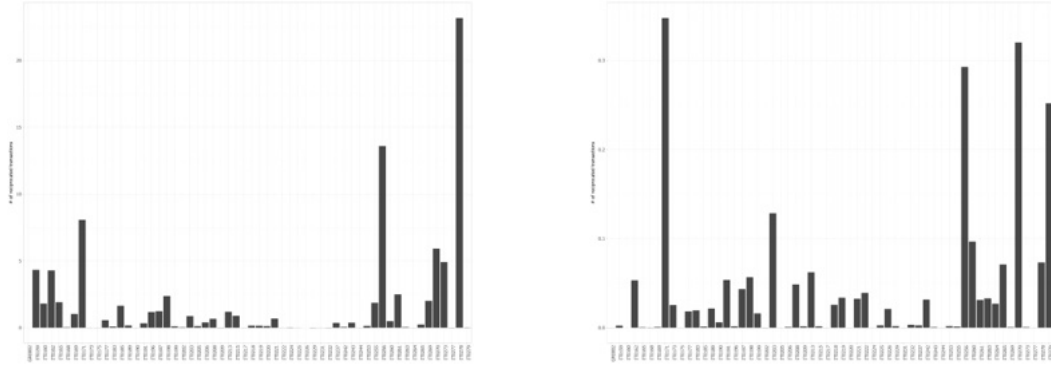


Fig. 3.8: Histogram of reciprocated transactions initiated in 2006Q1 and 2015Q4 by bank IT0258 as a liquidity provider.

that bank IT0258 engages in repeated and reciprocated trading instances with a very small number of partners.

3.4.2 Alternative models

The results for μ_t and ρ_t obtained under Model 3 and presented in the previous section can be compared to those obtained under Model 1, Model 2, and Model 4. With regard to μ_t , Model 2, as well as Model 1, seem to capture the essential features of volumes exchanged quarterly on the e-MID trading platform (Figure 3.10). In this regard, Model 2 is sufficient to capture the market drying up that progressively followed the turmoil that occurred in the summer of 2007. In providing a smoother representation of μ_t , Model 2 emphasizes that the market malfunctioning, first revealed in 2007Q3, had long-term and gloomy consequences.

Similar conclusions can be drawn by looking at ρ_t when estimated via Model 1 and Model 2 (Figure 3.11). Also in this case, the curve corresponding to Model 2 (Figure 3.10b) provides a detailed enough representation of the dynamics of reciprocity. In particular, ρ_t estimated under Model 2 (Figure 3.11b), clearly reveals the decreasing and increasing levels of reciprocity that followed the progressive emergence of the Global Financial Crisis and the intervention measures operated by the ECB, respectively.

A more detailed representation of both μ_t and ρ_t are certainly provided by Model 4 (Figure 3.12). However, Models 2 and 3 are flexible enough to isolate general trends in market connectedness and reciprocity. Therefore, the modeling effort required to introduce dummy variables is not justified.

3.5 Discussion and conclusions

Our analysis of the European interbank market has demonstrated the ways in which dyadic exchange, and reciprocal exchange as a particular case, manifest in financial networks over time. The reasons why we focus on the temporal dynamics of reciprocal exchange are specific to financial markets, here conceived of as examples of switch-role markets. First, reciprocal exchange naturally emerges in longitudinal settings. Second, reciprocal exchange develops in a context of role fluidity. As a consequence, our understanding of financial markets leads to the evaluation of trading relationships through individual related parameters. First, one parameter measures the amount of reciprocity

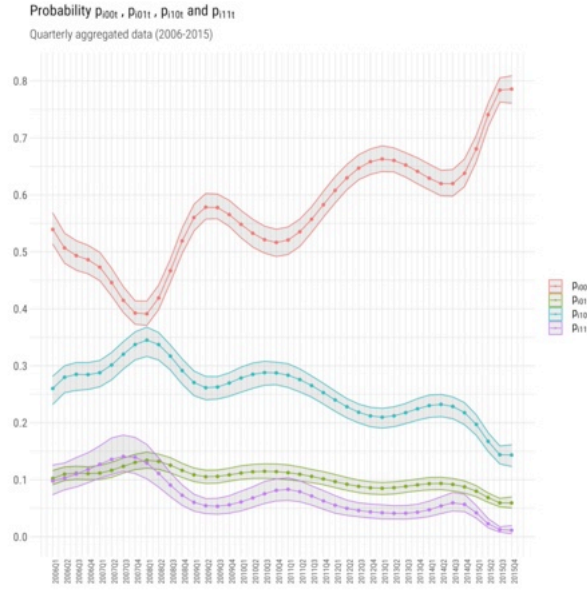


Fig. 3.9: Probability of bank IT0258 being involved in four different trading configurations. The light blue line p_{i10t} and the purple line p_{i11t} indicate the estimated probabilities of initiating a transaction as a liquidity seller and being reciprocated, respectively. The green line p_{i01t} represents the probability of acting as a pure receiver, while the red line p_{i00t} shows the probability of not being selected as a trading counterpart by any sender.

between nodes with respect to the average market propensity to reciprocity. Second, two parameters measuring the nodes' differential attractiveness as buyers and sellers.

We estimated the parameters of interest by considering a representative pair of actors and by adopting a latent trajectory modeling approach based on an iterative algorithm that maximizes the composite pairwise log-likelihood for every ordered pair of units. We defined the latent trajectories by referring to the four distinct specifications of dyadic exchange on the basis of splines and temporal dummy variables. Regardless of the illustrative case, the empirical merit of our methodological approach is twofold. First, it represents the process of exchange at a fine-grained level. Second, it can be used to investigate both systematic changes and inter-individual variability in behavioral tendencies that might be of general or contingent interest. The empirical application shows that the proposed methodology can be applied to large networks. Empirical results provide strong evidence for significant changes in patterns of dyadic exchange during the period of observation, thus signaling that the progressive emergence of the Global Financial Crisis had an impact on how liquidity providers related to their borrowing counterparties. A more detailed description of our results may be obtained by including nodal and edge covariates in the model.

Generalizations of the reported dyadic conditional distribution may relax the conditional independence assumed by the p_1 model and extend the model to account for other empirical regularities. For instance, an additional time-dependent parameter related to the difference between node in-degrees can capture negative assortativity and its evolution over time – that is, the empirical phenomenon for which nodes with few connections tend to link to highly-connected hubs. Similarly, a time-dependent parameter related to the number of triangles in which two nodes are involved accounts for the path-shortening tendency to observe closed triangles, favoring trades with banks having common partners. Also, a node-dependent parameter associated with differences in dyadic configurations over time

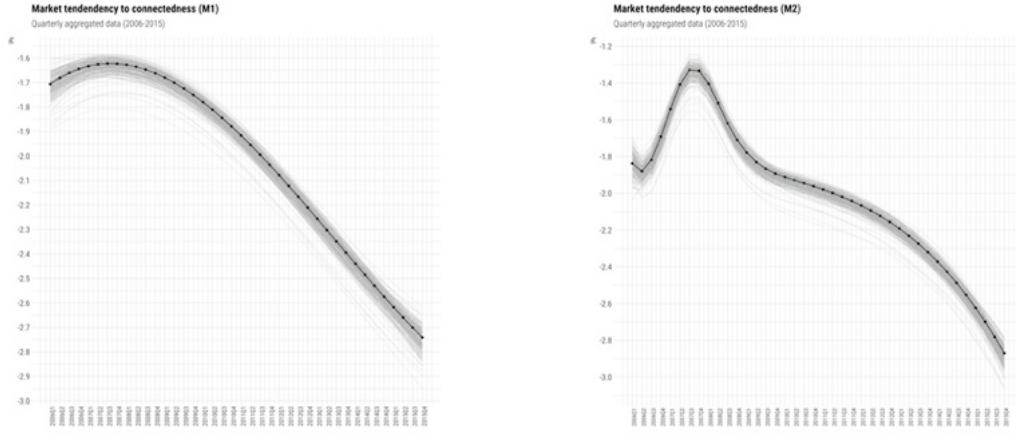


Fig. 3.10: Market tendency to connectedness obtained under Model 1 (polynomial of order 3) and Model 2 (spline with three nodes in 2007Q3, 2008Q4, and 2010Q2). Gray lines represent 250 bootstrapped trajectories.

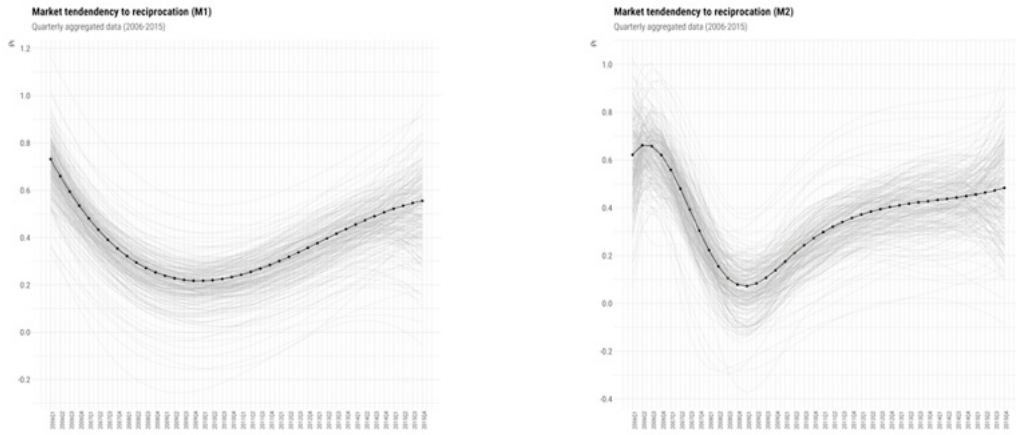


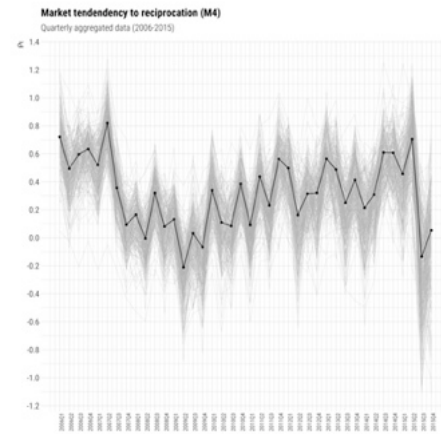
Fig. 3.11: Market tendency to reciprocity computed according to Model 1 (polynomial of order 3) and Model 2 (spline with three nodes in 2007Q3, 2008Q4, and 2010Q2). Gray lines represent 250 bootstrapped trajectories.

can explain the stability of the chosen partners of a bank. Another interesting line of extension is towards multi-type relationships, which are important in applications such as friendship or organizational networks, through multiple independent or dependent adjacency matrices, along the lines already suggested in Holland and Leinhardt (1981).

Finally, it may be of interest that a Bayesian extension of the framework is proposed. To overcome inherited computational complications, we can follow Dutta et al. (2017) through an Approximate Bayesian Computation (ABC) approach (Diggle and Gratton, 1984; Rubin et al., 1984; Tavaré et al., 1997). When ABC is applied to network models, the original dataset corresponds to the observed network G , and the latter is compared to the model-generated networks using appropriate summary statistics.



(a) Market tendency to connectedness.



(b) Market tendency to reciprocity.

Fig. 3.12: Market tendency to connectedness and reciprocity computed according to Model 4 (dummy variables on each period).

From ties to events in the analysis of exchange relations: The emergence of *network times*

4.1 Introduction

The theoretical premise that underlies this study is that a significant amount of information is lost when aggregating continuous-time interaction data into binary network ties observed at discrete time points. In this regard, this study shows that, when maintaining the natural timing of the interaction process, the social micro-mechanisms that emerge from continuous-time interaction data possess their own temporal structure, capable of reflecting time-specific variations in the relational activities underpinning network ties.

Data on continuous time interaction are routinely generated by participation in online communities (Golder and Macy, 2011), use of technology-mediated communication (Perry and Wolfe, 2013), and contributions to peer-production projects (Lerner and Lomi, 2019). However, access to continuous-time interaction data is becoming increasingly common, also in more traditional interorganizational settings, such as healthcare (Amati et al., 2019) and certain types of financial markets (Cocco et al., 2009; Iori et al., 2015). In all these cases, participants interact through a technological interface that produces and stores highly accurate continuous-time information on social interaction taking the form of sequences of directed *relational events* defined as: “discrete event(s) generated by a social actor (the “sender”) and directed toward one or more targets (the “receivers”)” (Butts, 2008, p.159). Ultimately, the time-stamped sequences of relational events that connect sending and receiving units crystallize into network-like dependencies, representing the observable micro-relational structure of networks.

Having at my disposal an exceptionally large collection of high-frequency transactions occurred on a major trading platform represents a unique opportunity to show that the micro-relational structure of interorganizational networks can be properly understood only in accordance with the arrangement of time – as the Greek philosopher Anaximander suggested a long time ago¹. Time is a measure of change and, as such, has profound importance in shaping the micro-relational structure of interorganizational communities (Amati et al., 2019; Kitts et al., 2017; Quintane et al., 2013). Explicitly accounting for the temporal component of basic “principles of organizational bonding” (Laumann and Marsden, 1982) has guided me to develop a deeper reflection on how network structure can be ultimately conceived of in terms of *network times*.

In the same vein, recent methodological studies on longitudinal networks have shown an increased awareness about the importance of temporal information in shaping the relational structure of interorganizational communities (Block et al., 2018; Stadtfeld, 2012), while an increasing collection of studies on interorganizational networks has stressed how social interaction exhibits important empirical regularities in distinct time frames (Amati et al., 2019; Kitts et al., 2017; Quintane et al.,

¹Simplicius, *In Arist. Phys.* 9.24.13

2013). Building on these recent advances, this study aims to show that, prior to any modeling effort, changes in connective behaviors can be appropriately interpreted only by examining the time-specific variations that affect the micro-mechanisms emerging from records of continuous-time interaction.

The empirical part of the current study documents that time-specific variations of the micro-relational structure are imputable to three distinct factors. The first source of variation in micro-mechanisms of connectivity is the *timing* of the relational events, that makes it possible to adjudicate agency (Gibson, 2003; Stadtfeld and Block, 2017) and ultimately assess the meaning of relational events for the agents involved – meaning that is not invariant to permutation of the events in time. The second source of variation refers to the *rates* at which relational events are emitted by the source organization toward its target(s). Patterns of interorganizational exchange happen at rates whose speed is dependent on features of the context and of the relation. For example, financial transactions typically occur at very high frequency, with a large number of actual events happening on short time scales, such as days or even hours. In contrast, strategic alliances, joint ventures, and similar intercorporate relations involve episodic relational events with a duration that is sometimes established by contract. The majority of interorganizational relations fall somewhat within these extreme cases, with streams of relational events connecting sender and receiver organizations unfolding at variable speeds. Amati et al. (2019), for instance, show that event rates involving patient referral relations between hospitals display significant daily variation. Finally, time-specific variations in network micro-mechanisms occur because such mechanisms do not operate instantaneously – that is, it takes time for local network configurations of theoretical interest to emerge and explicate their effects. When information on the *internal timing* of network mechanisms is taken into account, social interaction exhibits regularities in different time frames, thus making it possible to distinguish, for example, between short- and long-term effects (Kitts et al., 2017; Quintane et al., 2013). Kitts et al. (2017) demonstrate the importance of this distinction by specifying “dependence” and “embedding reciprocation”. The former embodies a logic of resource dependence, while the latter embodies a logic of resource sharing. Regarding the temporal component of reciprocation, Kitts et al. (2017) find that both dependence and embedding reciprocation work in the short term, but only embedded reciprocation works in the long term. In the same vein, Quintane et al. (2013) have shown that fundamental micro-mechanisms like reciprocation and transitive closure unfold with stable patterns of interaction both in the short- and in the long-run – in the short-run to adapt to change, and in the long-term to develop cohesion.

By examining the collection of overnight transactions that occurred on the e-MID trading platform between 2006 and 2015, the empirical part of this study presents a range of methods to reveal the temporal dynamics of social interaction. Focusing on the network times that define the dynamics of interaction on financial markets carries great merit. In fact, because their recordings are accurate to the second, financial transactions provide an almost ideal illustration of directed, continuous-time interaction, generating time-stamped sequences of relational events that connect sender and receiver units. Moreover, sequences of financial transactions illustrate particularly well the relation between micro-relational patterns of interaction between organizations and macro-structures of roles (Leifer, 1988; White, 1981), in this specific case, buyers and sellers of overnight liquidity contracts. Moreover, because of their extension over time, high-frequency sequences of financial transactions illustrate particularly well how micro-patterns of interaction between organizations evolve into macro-structures of roles and relationships (Leifer, 1988; White, 1981). This is particularly relevant, especially in the context of financial markets. Even if a few studies on financial networks have postulated that financial markets have an underlying micro-structure that arises from micro-networks of egocentric transactions (Baker, 1984; Cohen-Cole et al., 2015), none of them have recognized that the macro-structure of roles emerges endogenously through sequences of time-dependent transactions.

Throughout the analysis, the focus is kept on the dynamics of reciprocation and transitive closure, two fundamental micro-mechanisms of connectivity responsible for cooperation (Fehr and Gächter, 2000) and social cohesion (Friedkin, 2004; Granovetter, 1973). In particular, my narrower focus on reciprocation is justified by its theoretical significance and empirical relevance in interorganizational relations (Kitts et al., 2017), financial markets (Uzzi, 1999), and in economic exchange more generally Fehr and Gächter (2000). In organizational settings, the joint analysis of dyadic and triadic relational mechanisms is a well-established practice, as it provides valuable insights into the emergence of population-level structures. This occurs through the combination of dyads into triads, which, in turn, develop into larger structures of shared partners. The comparison between reciprocation and transitive closure is still meaningful when considering their temporal dynamics. In fact, for relational processes operating above the dyadic levels, it might be reasonable to expect a slower temporal development because they are constrained by the convergence of those dyadic processes that work as their antecedents. For phenomena such as the development of organizational clusters or the development of trust, the underlying process is usually inertial, with the obvious consequence that they might not adjust quickly to changes in the exchange scenario.

The analysis clarifies how reciprocation and transitive closure operate with significant differences over distinct exchange regimes and temporal frames. Empirical results show that these two micro-mechanisms do not operate in synchrony – i.e., the time necessary to observe a reciprocated transaction is typically different from the time required to observe a two-path closing into a transitive triad. On a more conceptual level, the findings presented in this chapter suggest a new theoretical interpretation of network structure as contingent and time-dependent because of the constraints imposed on current relational activities (Abbott, 1990; Chase, 1982; White, 1970) by the “the network of other cases and prior times” (Abbott, 1995, p.94). In this regard, despite the obvious limitation of a single empirical case, this study provides a valuable starting point for future research on the link between the variability of network micro-mechanisms and the variability of behavioral outcomes traditionally associated with those constructive relational micro-mechanisms.

4.2 Network micro-mechanisms and *network times*

Aggregating continuous-time relational events into binary network ties observed at discrete time points results in information loss regarding the sequence and timing of those relational events. In turn, avoiding consideration of temporal variations in the relational activities that underpin network ties represents a significant limitation in representing the actual structure of networks. Those general constraints are particularly restrictive in studies of financial markets, which are naturally conceived of as event networks composed of transactions that depend on one another over time. In fact, when dealing with financial networks, the transaction is both the constitutive element of the network and its finest-grained unit of analysis. Therefore, considering financial networks as sequences of time-ordered transactions that connect changing sets of buyers and sellers is the most obvious and accurate depiction of financial markets, and thus of markets in general.

A deeper understanding of the temporal dynamics of interaction patterns has been constantly informing the research agenda of network scientists (Butts, 2008, 2009; Perry and Wolfe, 2013; Rivera et al., 2010; Snijders et al., 2010; Stadtfeld et al., 2017; Vu et al., 2017). Yet, with the possible exceptions of a few studies (Amati et al., 2019; Kitts et al., 2017; Quintane et al., 2013) that consider the micro-mechanisms underlying the dynamics of interorganizational networks as time-dependent, time-focused theories of social processes are still missing from organizational literature (Ancona et al., 2001). In fact, most existing research on interorganizational networks typically views past structural

configurations as stable over indefinite temporal horizons. Data collection is often based on panel studies in which network ties are collected at regular points in time (Snijders et al., 2010; Snijders, 1990, 1996) and parameter estimates reflect relatively enduring forms of dependence among social units. In contrast, when time is explicitly assumed to shape network structure and the social process of interest is documented by continuous time interaction data, a rigorous longitudinal analysis requires a proper interpretation of the micro-mechanisms that emerge from time-ordered sequences of relational events.

The empirical case at hand does not represent an exception. Therefore, the link between “continuous relations” and “social networks” (Butts, 2009; Mische, 2011) is established by the micro-mechanisms that emerge from time-stamped transactions and ultimately reveal the system of positions and mutual obligations that clearly entail exchange relations. A promising way to make sense of those micro-mechanisms is conceiving of them as a collection of enchainned and non-permutable (Abbott, 1983) conversational encounters (Gibson, 2003, 2005, 2008). In addition to regular conversations, “money talks” refers to followable stories, which means that prior instances of conversations or transactions influence subsequent conversational or transactional dynamics. Consider, for instance, reciprocation – a relational mechanism of central importance in theories of exchange (Molm et al., 2003) and substantive interest in empirical studies of interorganizational relations (Ingram and Roberts, 2000; Uzzi, 1996). Clearly, the effect and meaning of reciprocity are not invariant to change in the sequential ordering of the underlying events that define it. The correct identification of who is initiating action and who is reciprocating – and when – may matter greatly not only because sequential ordering in social interaction provides important information about status differences and dominance relations (Chase, 1982; Gibson, 2005), but also because of the path-dependence that social interaction induces (Gibson, 2011). Reciprocated exchange has an internal time distribution that is subject to high contextual variability. Like other, more complex, relational mechanisms involving more than two actors (Nowak and Sigmund, 2005), direct reciprocation emerges over periods of variable length, in which the time scale may vary from a few minutes for communication in emergency situations (Butts, 2008), days for email communication (Perry and Wolfe, 2013), and months for complex interorganizational exchange (Kitts et al., 2017). A similar argument holds for a more complex structure of dependence involving three or more social units. Consider, for example, triadic closure – a key mechanism in the building of social structure (Burt, 1992; Coleman, 1988; Granovetter, 1982; Uzzi, 1996, 1997) and an indicator of cohesiveness (Friedkin, 2004; Granovetter, 1973). To observe an event generating transitive closure between a sender and a receiver, other events involving the same two actors in two-path-like structures must have occurred. Within an organizational context, transitive closure can also represent the need for organizations to coordinate their activities (Quintane et al., 2013) in order to pursue both contingent and long-term objectives. In this guise, the transitive closure is intended to reflect a more time-sensitive structure than reciprocation, capable of unfolding both within short-term and long-term frames.

Under conditions of time-specificity and sequential constraints, relational data obtained by aggregating relational events into ties may lead to biased conclusions about tendencies toward reciprocity and transitive closure, depending on the “internal clock” that regulates these relational mechanisms in the specific circumstances of interest. By considering social networks as the “pattern of regular exchange connections that actors recognize as important to their activity” (Rank et al., 2010), I implicitly admit the value of investigating regularities in connective micro-mechanisms from a temporal perspective that allows connective behavior not to unfold independently of the timing of the relational events it emerges from. Ultimately, combining the interactional foundations of relational activities with the time-specific variations in micro-relational mechanisms holds great merit. This is the first


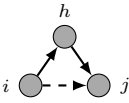
empirical study that actually documents the presence of “network times” (Stark and Vedres, 2006) and “rhythms of social interaction” (Golder et al., 2007) and accordingly lays the groundwork for a proper modeling approach based on directed social interaction data (Vu et al., 2017) and accounting for the time-specific variations in relational mechanisms that have generated the observations. Chapter 5 of this dissertation moves exactly in this direction and derives hypotheses about the types of network effects that may be more or less sensitive to time-specific variations under conditions of uncertainty affecting partner selection strategies.

4.3 The internal timing of reciprocation and transitive closure

To make the temporal component of micro-mechanisms emerge, I rely on the seminal work of Butts (2008, p.160) and accordingly assume that “past history creates the context for present action, forming differential propensities for relational events to occur”. This principled framework sees each relational event in the sequence as a function of the history of past interaction up to that moment in time. So, once a relational event occurs, “this alters the context of action, and the process begins anew” (Butts, 2008, p.160). Conceptually, this means that the emergence of future interaction is not completely determined by the history of past interaction, but rather it is influenced by the timing of different patterns of past interaction.

These theoretical considerations have encouraged me to capture the timing of reciprocation and transitive closure by computing the so-called *time to reciprocation* and *transitive closure*. The network micro-mechanisms of reciprocation and transitive closure are portrayed in Tab. 4.1 along with their underlying formulas. Let $N_{ij}(t^-)$ be the number of relational events between sender i and receiver j right before the time t , and T_{ij}^e the time at which a relational event e between i and j occurred. In both cases, the micro-mechanisms of interest are functions of time as Tab. 4.1 documents.

Tab. 4.1: Definition of reciprocation and transitive closure

Micro-mechanism	Representation	Formula
Reciprocation		$\sum_{e=1}^{N_{ij}(t^-)} f(t, T_{ji}^e)$
Transitive closure		$\sum_{h \neq i, j} \left(\sum_{e=1}^{N_{ih}(t^-)} f(t, T_{ih}^e), \sum_{e=1}^{N_{hj}(t^-)} f(t, T_{hj}^e) \right)$

For a potential relational event connecting the sender i to the receiver j ($i \rightarrow j$) at time t_1 , the *time to reciprocation* is the time necessary to observe a relational event in the opposite direction ($j \rightarrow i$) at a later time t_2 , namely the difference between t_2 and t_1 . For an observed open two-path ($i \rightarrow h \rightarrow j$) at time t_1 , the *time to transitive closure* is the time required to close that two-path via a relational event connecting the sender i to the receiver j at a later time t_2 , namely the difference between t_2 and t_1 . In both cases, the quantities of interest are computed by taking into account the structure of the network and the passing of time. Therefore, all the events occurring at the representative time t_2 can reciprocate and close multiple corresponding relational events that have occurred at an earlier time t_1 . Especially for the transitive closure, computation can be intensive, and custom-developed

Python routines have been implemented to compute the number of open and closed two-paths, along with their corresponding times.

As the empirical analysis of this study shows, times to reciprocation and transitive closure have been computed across discrete time periods corresponding to market-level shifts in exchange regimes and meaningful time frames – as it is extensively documented in Chapter 3. Regarding reciprocation, in a network of 504,576 transactions, there are 10758 reciprocated exchange instances. As Fig. 4.1 shows, the proportion of reciprocated dyads does not considerably differ across meaningful time frames. Shorter time frames are defined in light of the trading rules and routines adopted on the e-MID platform, open to trading five days a week, and mostly used to extend overnight loans. Longer time frames refer to periods in which the trading activity is regularly monitored by the ECB. The indicative calendar for the Eurosystem operations includes “main refinancing operations” (MROs) approximately every 30 days, and “three-month longer-term refinancing operations” (three-month LTROs) every 90 days². Interestingly, at least 75% of transactions are reciprocated within 90 days, the larger time frame in which the trading activity on the European interbank market is monitored by the ECB, while approximately half of transactions are reciprocated by 30 days. This simple representation of the time to reciprocation clearly shows that both short-term (1 and 5 days) and long-term time frames (30 and 90 days) are worth considering when analyzing social micro-mechanisms with a specific attention to their temporal patterns.

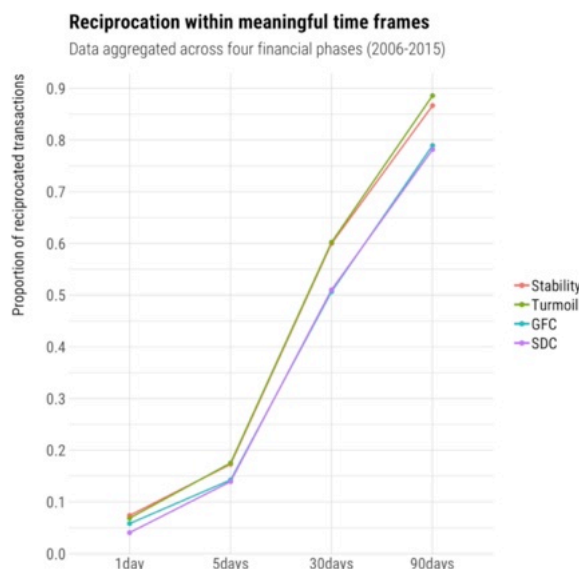


Fig. 4.1: Proportion of reciprocated transactions within meaningful time frames

With a greater variability, the same conclusions that emerge from Fig. 4.1 substantially hold for transitive closure, whose temporal dynamics across the same time frames is depicted in Fig. 4.2. In a set of 6,023,960 closed two-paths, the generous proportion of transitive triads that close within 30 and 90 days reveals that the trading activity on the e-MID platform closely aligns with the indicative calendar issued by the ECB, aimed at monitoring the European interbank market. Altogether, these preliminary results show that for both the micro-mechanisms of interest, it makes sense to study their time-specific variations within a temporal frame no longer than 90 days.

²<https://www.ecb.europa.eu/press/pr/date/2018/html/ecb.pr180711.en.html>

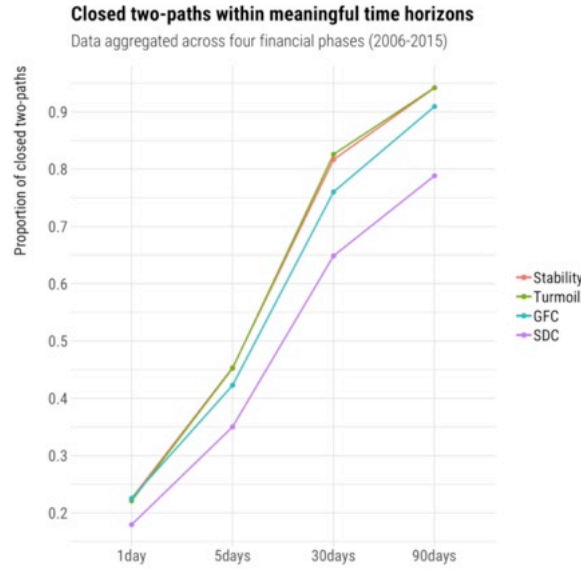


Fig. 4.2: Proportion of closed two-paths within meaningful time frames

Keeping the focus on Fig. 4.1 and Fig. 4.2, the partial but distinct overlapping between curves reveals two crucial aspects of time-specificity in interbank transactions. First, both short- and long-term time frames exhibit regularities in their temporal patterns. Second, regularities that pertain to the short-term do not necessarily carry over to regularities observed in the long-term. Furthermore, distinguishing four distinct financial phases within the whole period of observation – which is made possible by the quasi-experimental nature of the data – adds another layer of complexity to the understanding of time-specific variations in relational mechanisms. In this regard, a comparison between Fig. 4.1 and Fig. 4.2 clearly shows that reciprocation and transitive closure do not work in synchrony during periods characterized by heterogeneous scenarios for economic dynamics and exchange regimes. This latter consideration finds empirical support in Fig. 4.3 and Fig. 4.4, depicting the internal timing of reciprocation and transitive closure, respectively. On the one hand, to obtain a proper graphical illustration of the empirical results, I report the internal time distribution of reciprocation and transitive closure by considering 75% of observations. On the other hand, I introduce the corresponding summary statistics referring to the whole sample in Tab. 4.2 and Tab. 4.4. Comparing Fig. 4.3 and Fig. 4.4, it clearly emerges that reciprocation and transitive closure are both right-skewed, even if open two-paths tend to close into transitive triads much faster than simple dyadic transactions actually do. This finding, whose details are shown in Tab. 4.2 and Tab. 4.4, is in stark contrast with studies postulating that extra-dyadic structural processes unfold, at least, as fast as their dyadic counterparts (Kitts et al., 2017). However, these surprising results might be coherent with some structural features of the e-MID network, like the presence of a strongly connected group of banks that act as global hubs for the whole network (Iazzetta and Manna, 2009) by connecting the core to the periphery of the network (Fricke and Lux, 2015). Furthermore, in both cases, the emergence of the Global Financial Crisis in September 2008 seemed to influence the way European banks traded with their peers. Beyond the similarities, as a set of Kolmogorov-Smirnov tests reveals, the internal time distributions of reciprocation and transitive closure are statistically different ($p\text{-value} = 2.2e-16$). I also found significant differences when examining the internal time distributions across the four financial phases. The time to reciprocation during the GFC differs from that measured during the previous ($p\text{-value} = 8.5e-14$) and following ($p\text{-value} = 0.1507$) financial periods. In the same vein,

the time to transitive closure during the GFC differs from that measured during the stability/turmoil (p-value = 2.2e-16) and the SDC (p-value = 2.2e-16) periods.

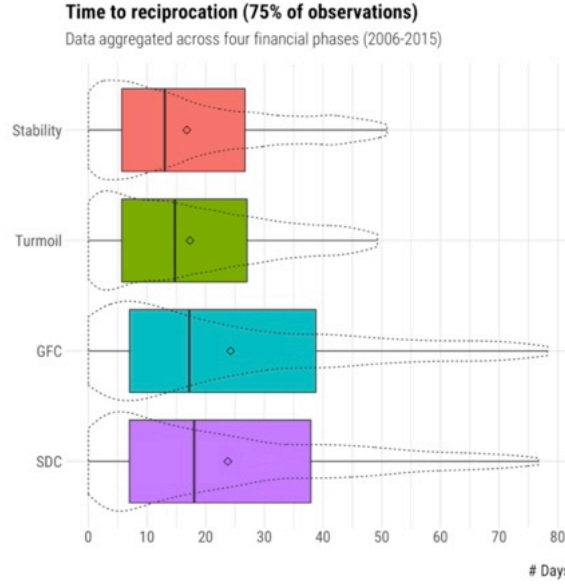


Fig. 4.3: Internal time distribution of the time to reciprocation

Tab. 4.2: Time to reciprocation: summary statistics

Phase	Time to reciprocation					
	Min	Q1	Q2	Mean	Q3	Max
Stability	0.000	7.236	20.279	43.579	50.896	482.747
Turmoil	0.001	8.041	21.956	39.026	49.533	324.096
GFC	0.001	9.758	29.050	59.416	78.261	576.231
SDC	0.002	9.973	28.801	80.194	76.741	1434.802

A more detailed representation of transitive closure is offered by its normalized version, computed by dividing the time to transitive closure by the time necessary to observe their antecedent two-paths. In other words, given three social units (i, h, j) connected in dyads at three distinct points in time as $(i \rightarrow h)$ at t_1 , $h \rightarrow j$ at t_2 , and $(i \rightarrow j)$ at t_3 , the quantity of interest is computed via $(t_3 - t_2)/(t_2 - t_1)$ with $t_1 < t_2 < t_3$. In doing so, I no longer obtain a temporal measure, but this measurement helps me understand how quickly two initially unconnected nodes (i and j) establish a connection when they share a third party (h) in common. Values greater than 1 mean that open two-paths collapse into transitive triads slower than their corresponding antecedents, while values smaller than 1 indicate an opposite tendency. The output in Fig. 4.5 shows that, in all four financial phases, approximately 80% of normalized measurements are smaller than 1, thus revealing that two unconnected nodes are more prone to establish a direct link once they are separated by one mutual intermediary.

Also in this latter case, Kolmogorov-Smirnov tests, computed by comparing the GFC period with the previous stability/turmoil periods and the following SDC period, reveal that the distribution of the normalized time to transitive closure is different over the exchange regimes defined by the emergence of the GFC (p-value = 2.2e-16 in both cases). More interestingly, this measure decreases as the economic scenario worsens – that is, during the GFC and SDC periods – and increases as

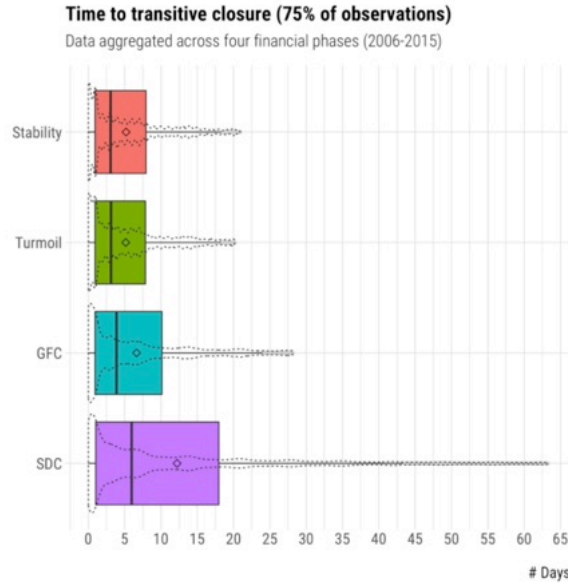


Fig. 4.4: Internal time distribution of the time to transitive closure

Tab. 4.3: Time to transitive closure: summary statistics

	Time to transitive closure					
Phase	Min	Q1	Q2	Mean	Q3	Max
Stability	0.000	1.060	6.043	21.305	20.878	559.987
Turmoil	0.000	1.092	6.032	21.574	20.134	399.971
GFC	0.000	1.067	7.071	28.811	28.114	585.201
SDC	0.000	2.155	12.755	102.048	63.230	1974.024

Tab. 4.4: Time to transitive closure: summary statistics

soon as financial turmoil arises in August 2007. Jointly with the output depicted in Fig. 4.4, these results seem to suggest that, in the presence of a deteriorated economic environment, European banks initially took some time to effectively check the creditworthiness of their peers. However, once credit institutions have recognized the soundness of their connections, they are more likely to exchange liquidity within smaller clusters of banks that comprise their partners' partners.

The final step in understanding the existence of time-specific variations in relational micro-mechanisms is to compute the Kaplan-Meier estimator (Kaplan and Meier, 1958) for the time to reciprocation and the time to transitive closure across the four financial phases. The events of interest or deaths are represented by the time to reciprocation and transitive closure, which have been paired with their censored counterparts. For the time to reciprocation, censored data are represented by the internal times of transactions that have never been reciprocated. Similarly, for the time to transitive closure, censored data are given by the internal time of two-paths that have not closed into transitive triads. In both cases, the survival times associated with the censored data are given by the time difference between the end date of each financial phase and the time associated with the censored events.

The estimator of the survival function $S(t)$ – that is, the probability that life is greater than t is given by:

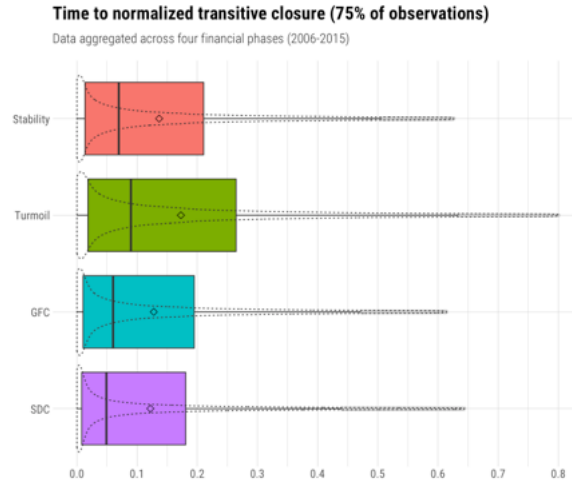


Fig. 4.5: Internal time distribution of the time to transitive closure normalized by the time necessary to observe the antecedent two-path

$$\hat{S}(t) = \prod_{i:t_i \leq t} \left(1 - \frac{d_i}{n_i}\right),$$

with t_i a time when at least one event occurred, d_i the number of events (deaths) that happened at time t_i , and n_i the units known to have survived up to time t_i .

All the Kaplan-Meier curves are reported on the same plot in order to facilitate the comparison of the probability of survival across the four financial phases. For the same reason, confidence intervals are not reported but computed by using robust standard errors. Results referred to the probabilities of survival within a temporal horizon of 30 days are reported below in Tab. 4.5 for the time to reciprocation and in Tab. 4.6 for the time to transitive closure. The corresponding 95% confidence intervals are also reported.

For the time to reciprocation, Kaplan-Meier estimates are reported in Fig. 4.6. A log-rank test confirmed that survival curves for the time to reciprocation are statistically different across the four exchange regimes (p-value = 2.2e-16). The notable differences among the survival curves suggest that the progressive emergence of the Global Financial Crisis has led to multiple changes in trading behavior. If I restrict my attention to temporal frames that are meaningful for the regular trading activity on the eMID market, I notice that, when the global economic scenario got worse, the tendency to reciprocation progressively increased, as Tab. 4.5 documents. The differences among the Kaplan-Meier curves became stronger for longer time frames, thus signaling that the market micro-mechanisms took time to adjust to fluctuations and changes in the exchange environment.

Kaplan-Meier survival curves for the time to transitive closure are depicted in Fig. 4.7. An equally weighted log-rank test for between-groups differences shows that Kaplan-Meier survival functions for the time to transitive closure differ across the four exchange regimes (p-value = 2.2e-16), even if the Kaplan-Meier curves referred to the first three periods are partially overlapping. Such an overlap can be taken as a signal that transitive closure is a more dynamic and time-sensitive micro-mechanism, capable of adjusting to fluctuations also in the short term, as Tab. 4.6 shows. Regarding long-term differences, Fig. 4.7 documents that the tendency to transitive closure substantially changed only

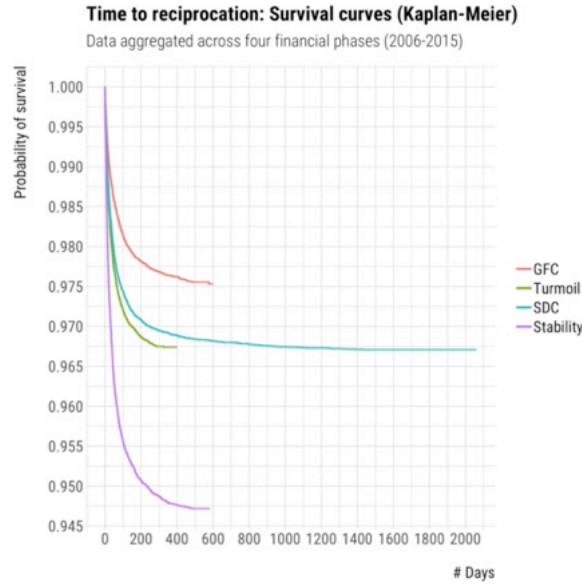


Fig. 4.6: Kaplan-Meier survival probabilities for the time to reciprocation

Tab. 4.5: Kaplan-Meier survival probabilities and the corresponding 95% confidence intervals for the time to reciprocation after 30 days

Phase	Time to reciprocation		
	Pr. survival	95% CI	
Stability	0.9706	[0.9695,	0.9718]
Turmoil	0.9820	[0.9809,	0.9830]
GFC	0.9888	[0.9879,	0.9896]
SDC	0.9837	[0.9829,	0.9844]

during the last period of observation, once the economic scenario was stuck in a deep crisis. During the SDC period, the general market activity decreased, with the obvious consequence that more two-paths stayed open.

When combining the results of the two sets of Kaplan-Meier curves, it clearly emerges that the internal time distributions of reciprocation and transitive closure react differently to changes in the economic scenario. For instance, when moving from the stability to the turmoil phase, after 30 days the tendency to reciprocation decreases, while the probability of closing a two-path increases. Taken together, these results shed light on the population-level structure. Reciprocation and transitive closure, in fact, are sufficient to produce evidence on generalized exchange. In this specific case, the combination of dyads that do not tend to reciprocate and two-paths that collapse into transitive triads causes local patterns of exchange to aggregate into a hierarchical structure at the population level.

Finally, the values of survival probabilities based on Kaplan-Meier estimators enable us to understand reciprocation and transitive closure in relation to their underlying mechanisms. On the one hand, the high values of survival probabilities for the time to reciprocation indicate that the proportion between reciprocated and non-reciprocated transactions is highly unbalanced, with a much larger number of non-reciprocated transactions, especially for shorter time frames. Even if with caution,

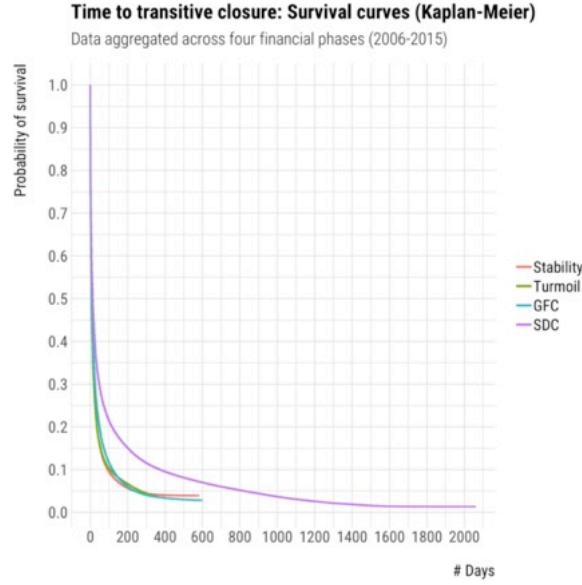


Fig. 4.7: Kaplan-Meier survival probabilities for the time to transitive closure

Tab. 4.6: Kaplan-Meier survival probabilities and the corresponding 95% confidence intervals for the time to transitive closure after 30 days

Time to transitive closure			
Phase	Pr. survival	95% CI	
Stability	0.2236	[0.2230,	0.2241]
Turmoil	0.2217	[0.2209,	0.2225]
GFC	0.2705	[0.2696,	0.2714]
SDC	0.3631	[0.3624,	0.3637]

results presented in Fig. 4.6 seem to suggest that tendencies to reciprocity are likely to unfold on longer temporal horizons, maybe sustained by long-term and embedded relationships (Uzzi, 1996, 1997), developed thanks to short-term sticky transactions. On the other hand, smaller values of survival probabilities for the time to transitive closure indicate a more balanced relationship between the number of closed and open two-paths, with a surprisingly larger number of closed transitive triads. In general, the propensity to transitive closure is strong in all the phases, both within short- and long-term time frames. In my reference setting, global tendencies to transitive closure signal that European banks alternatively activate and deactivate complex patterns of coordination in order to satisfy their liquidity needs or those of their peers. The time frames in which these complex patterns of coordination develop are crucial to understanding the dynamic nature of liquidity exchange on the e-MID trading platform over distinct exchange regimes. In particular, the presence of long-run tendencies towards transitive closure is a sign that certain contingent coordination patterns persist over the long term and therefore provide evidence of cohesive exchange dynamics between a selected group of core financial institutions.

All together, the results outlined in this section provide strong empirical evidence that the time frame of the global financial crisis depicted by Drudi et al. (2012) allows the time-specific variations of relational mechanisms to emerge. Moreover, the empirical evidence of regularities in interactions across

both short and long time frames suggests a certain level of flexibility in the network social structure, which would not be captured by aggregating continuous data on high-frequency transactions into arbitrarily inferred relational ties. Statistically significant differences in the internal time distributions of reciprocation and transitive closure reveal a set of stylized but crucial facts. First, different relational mechanisms unfold according to different time scales. Second, the same micro-mechanism exhibits statistically different internal time distributions across the financial phases.

4.4 Discussion and conclusions

The mixture of theoretical considerations and empirical evidence discussed in the prior sections clearly reveals the presence of temporal variations in the micro-mechanisms that describe the micro-relational structure of financial markets – namely, the relational structure that emerges from time-dependent individual transactions. This preliminary study on *network times* suggests that time, possibly defined at a high-level resolution, is worthy of being included as the primary contextual factors that influence the formation of exchange relations in financial markets characterized by high-frequency trading. On the one hand, the empirical implications of this claim are already evident in this study, which demonstrates, overall, the richness of the interpretation of social mechanisms that emerge from continuous-time interaction. Reciprocation, for instance, when emerging for sequences of time-ordered transactions, takes the form of a dynamic social process rather than an attribute of mutual exchange (Emerson, 1972). In the same vein, transitive closure is not only an indicator of network cohesion but rather a social process that reveals the more time-sensitive coordination requirements of organizational activities. On the other hand, from a methodological perspective, this analysis requires the development of a suitable event-oriented research design that can capture the time-specific variations in the micro-mechanisms that may have generated the observations. Chapter 5 moves exactly in this direction and provides a newly derived relational event model capable of providing parameter estimates representing interorganizational relations that unfold simultaneously across distinct time frames and exchange regimes.

The presence of *network times* in the micro-relational structure of financial markets – and thus of markets in general – raises theoretically related issues that deserve further attention. First, why time-specific variations in network social mechanisms matter in the analysis of exchange relations. Second, what are the possible sources of those time-specific variations. The current study provides an answer to the first question by claiming that analyzing the market micro-relational structure at the same granularity level as its foundational units enables a proper interpretation of the observed aggregate regularities in financial networks (Powell et al., 2005). In the European interbank market, for instance, such regularities might refer to the presence of a tightly connected core of banks acting as global hubs for the whole network (Iazzetta and Manna, 2009), assortative ties (Finger et al., 2013), and core-periphery structures (Fricke and Lux, 2015). Regarding the possible causes of time-specific variations in relational mechanisms, these are very much specific to the empirical setting at hand. Traditional explanations, such as the presence of resource constraints and information asymmetries (Amati et al., 2019), do not obviously apply to fully transparent markets like the e-MID trading platform, where banks can satisfy their contingent liquidity needs in a matter of minutes or even seconds. For this reason, in Chapter 5, I develop my own set of conjectures to test the presence of market uncertainty as a possible source of time-specific variations in the relational mechanisms that guide banks in the selection of their trading partners.

In more abstract terms, this study provides empirical evidence of the idea that “temporality of the market is the key” (Aspers, 2011, p.22) to make the relational structure of any market emerge. Ac-

cordingly, through the proposed analytical framework that links the market relational structure to the micro-mechanisms emerging from the record of actual transactions, this study also encourages reflection on the foundational micro-mechanisms of such a structure. The relational structure of markets typically consists of two roles: buyers and sellers. However, when these roles are not preassigned, they are acquired through interaction (Leifer, 1988). This is exactly the case of financial markets, in which buyers and sellers *switch* their *role* through the record of actual transactions, thus making it possible, eventually, to map the structure of roles onto its foundational micro-mechanisms. In this regard, a collection of reciprocated transactions represents the main relational mechanism behind role-switching, thus making reciprocation the foundational mechanism of financial markets. The importance of studying reciprocation as a dynamic process associated with role-shifting is twofold. On the one hand, the delay between two directed transactions distinguishes roles and posits the basis for interpreting aggregate tendencies of exchange behavior that are independent from the role identities. On the other hand, when the probability of interaction is high, reciprocation naturally evolves into extra-dyadic micro-relational mechanisms that are crucial for the functioning of decentralized markets. Building on this principled framework, in Chapter 5 I interpret the short- and long-term variations in reciprocation and transitive closure in terms of the role dynamics that they naturally entail.

The Effects of market uncertainty on exchange structures

5.1 Introduction

Organizations do not operate in stable contexts and typically strive to reduce the uncertainty generated by endogenous changes and fluctuations in their environment. Sociologists of organizations first noted that the structural arrangements of organizational design are core issues in managing uncertainty (Simon and March, 1957; Thompson, 1967). Later on, transaction cost researchers have claimed that organizations respond to uncertainty by moving transactions from markets to hierarchical contexts (Williamson, 1975, 1981, 1985). In the same vein, resource-dependence theorists have argued that organizations face uncertainty by transforming exchange relations into power relations, thus implicitly removing them from the market (Burt, 1983; Pfeffer and Salancik, 1978). More recently, some economic sociologists have emphasized the link between uncertainty reduction strategies and formal interorganizational networks, thus considering uncertainty as a driver of exchange partner selection (Beckman et al., 2004; Podolny, 1994).

When studying exchange partner selection strategies to survive uncertainty, this new line of research (Beckman et al., 2004) has emphasized the role of firm-specific and market uncertainty in affecting the choice of network partners. When faced with market uncertainty, organizations are more likely to exploit existing network ties rather than explore new alternatives. Interestingly, when faced with firm-specific uncertainty, organizations continue to refrain from broadening their network (Podolny, 1994), thus creating new relationships only in extreme circumstances.

Despite the study by Beckman et al. (2004) casting the study of interorganizational relations in a more dynamic light, none of the current studies have actually considered that organizations select their partners also on the basis of others' choices. And, this is even more true under conditions of market uncertainty when organizations struggle to properly interpret the stimuli that markets emanate. Therefore, limiting partner selection strategies to the repetition or simple broadening of existing exchange relationships strongly reduces the portfolio of available options.

Building on this premise, this study departs from previous work on partner selection strategies under uncertainty in two ways. First, this study explains that uncertainty also affects indirect micro-mechanisms of connection. These indirect relational mechanisms involve various forms of extra-dyadic patterns of connections, whereby the presence of indirect connections between two organizations makes them more likely to become directly connected (Lomi and Pallotti, 2013; Uzzi, 1997). Second, this study shows that the effects of market uncertainty are revealed across distinct phases. On the one hand, when the signals of uncertainty can be anticipated and organizations try experimenting with alternative strategies (March and Olsen, 1979; Weick, 1996). On the other hand, when the market effects of uncertainty are fully displayed and organizations progressively adapt and react to changes (Miles et al., 1978; Sine and David, 2003; Tao et al., 2014; Weick, 1996). Moreover, while organizational activities have been documented to change across the phases defined by the

emergence of environmental jolts (Meyer, 1982), there has been no similar discussion about market relationships.

Financial markets are ideal settings to explore the emergence and contextual effects of market uncertainty. In fact, regardless of the emphasis placed on market stability, the emergence of recent financial crises has led to a series of economic slowdowns that, in turn, have severely tested the integrity and resilience of financial institutions. In the current study, I restrict my focus to changes in the relational structure of financial markets, here defined in terms of roles and exchange relationships. In contrast to previous studies that have focused either on buyers' (Akerlof, 1970) or sellers' choices (Brunsson and Tyllström, 2018; Dyer, 1996), I detect changes in the relational structure of financial markets by focusing simultaneously on both sides of the market. This is possible because financial markets are examples of *switch-role markets*, namely markets in which the roles of buyers and sellers are not preassigned (Aspers, 2011) but rather acquired through the interaction (Leifer, 1988) among traders that auction securities on the trading floor. Under such circumstances, uncertainty reduction strategies equally involve the participation of buyers and sellers. As long as traders can be identified based on their contingent roles, interaction reduces market uncertainty through a repertoire of repeated actions, built on practice and experience.

The idea that uncertainty is mutually reduced for both trading counterparts through role-switching is new, as is the principled analytical framework adopted to illustrate this claim. Partners' selection strategies aimed at reducing uncertainty are illustrated by means of micro-mechanisms that directly emerge from the continuous interaction of buyers and sellers on the trading floor. Examples of micro-mechanisms that might reveal uncertainty reduction strategies are preferential attachment, inertia, reciprocity, assortativity, and multiple forms of triadic closure (Lomi and Pattison, 2006; Powell et al., 2005; Rivera et al., 2010). Building on early research on networks and uncertainty (Podolny, 1994), my study does not simply depict dependencies among organizations, but models these dependencies directly, expressed in the form of structural effects that encode various forms of dependence.

I demonstrate the empirical merit of this view, which connects uncertainty to role-switching, using data from more than 500,000 financial transactions observed on the e-MID trading platform between 2006 and 2015. To make sense of the role-switching induced by the emergence of market uncertainty, I examine how network micro-mechanisms in which financial transactions are embedded change over time. I utilize the quasi-experimental research design developed in response to the recent financial crises to identify four discrete time periods corresponding to market-level shifts in exchange regimes (Drudi et al., 2012). Accordingly, I investigate period-specific variations in network-based mechanisms. I narrow my analytical focus on two specific micro-mechanisms. First, I examine the role of reciprocation as a recognized mechanism influencing trust and expectations of repeated exchange among organizations, and as a major uncertainty-reduction strategy in partner selection. Second, I analyze the role of transitive closure as a key mechanism in the building of social structure (Burt, 1992; Coleman, 1988; Granovetter, 1982; Uzzi, 1996, 1997), and as a well-known indicator of market cooperation and cohesiveness (Friedkin, 2004; Granovetter, 1973). I adopt a newly derived version of relational event models to examine how tendencies toward reciprocation and transitive closure change over time, and to distinguish between long- and short-term reciprocity.

The paper is organized as follows. Section 5.2 discusses how dyadic and extra-dyadic micro-mechanisms might reflect partner selection strategies. Section 5.3 narrows the analytical focus by introducing a set of hypotheses that explain how reciprocation and transitive closure might behave under conditions of market uncertainty. Section 5.4 presents some empirical evidence on reciprocation and market activity. Section 5.5 introduces the relational event model whose empirical estimates are discussed

in Section 5.6. Finally, Section 5.7 concludes by discussing the implications of the current study in the context of contemporary research on the dynamics of interorganizational relations.

5.2 Network micro-mechanisms and exchange strategies

The idea that uncertainty reduction strategies emerge through the interaction between switching-role buyers and sellers can be captured by representing financial markets as evolving relational systems (Baker, 1984, 1990; White, 1981). In this guise, their evolutionary dynamics can be seen as an outcome of interdependent micro-mechanisms that regulate the reproduction and change of exchange relations among ordered pairs of organizations (Laumann and Marsden, 1982).

Using this mechanism-oriented approach, my study reconstructs the temporal dynamics of uncertainty reduction strategies by directly modeling sequences of high-frequency transactions observed in the form of social interaction in continuous time. The creation, the dissolution, and the reinforcement of individual exchange relations are described in terms of two classes of micro-mechanisms (Baum et al., 2003; Davis et al., 2003; Kogut and Walker, 2001; Powell et al., 2005; Rosenkopf and Padula, 2008). The first class of mechanisms controls direct connectivity, which refers to the tendency of organizations to choose and be chosen as exchange partners by their peers. The second class of mechanisms regulates closure, or *path-shortening behavior* – that refers to the propensity of organizations separated by one or more common third parties to become directly connected.

In directed interorganizational systems, direct connectivity mechanisms include, for instance, preferential attachment, inertia, reciprocity, and multiple forms of assortativity (Powell et al., 2005).

Preferential attachment is a general concept referring to the tendency of central organizations to become more central in a degree sense (Stuart, 1998; Stuart and Yim, 2010). It can be measured in terms of intensity – the tendency of organizations to create relations with partners – and popularity – the tendency of organizations to be selected as partners. The main implication of preferential attachment is that network nodes establish new edges as a function of edges they have already established (Newman, 2001). For this reason, empirical studies on interorganizational networks interpret preferential attachment as a process that confers network nodes an accumulative advantage resulting in different logics of connectivity (Powell et al., 2005), or prominence in an organizational field (Rosenkopf and Padula, 2008).

Inertia refers to the tendency of organizations to repeat their ties, or the relational events connecting them (Vu et al., 2017). The persistence of network ties or patterns of repeated events is a key element of social networks and, therefore, of relational systems in general (Freeman et al., 1987). Because of that, empirical studies on interorganizational networks have interpreted inertia as a condition for developing trust between partners (Gulati and Nickerson, 2008) and as a process leading partner selection strategies in the case of uncertainty (Beckman et al., 2004; Podolny, 1994).

Reciprocity refers to the tendency of organizations to establish symmetric ties, or patterns of relational events in which senders and receivers exchange resources by switching their initial roles (Vu et al., 2017). Organizational studies often interpret reciprocity as a signal of stability in interorganizational relations since non-reciprocated relations have an intrinsic tendency either to become symmetric or to vanish (Rivera et al., 2010). Moreover, reciprocity has been extensively paired with individual attempts to reduce or avoid uncertainty due to its capacity to trigger mutual control, expectations, and obligations (Coleman, 1988; Laumann and Marsden, 1982; Uzzi, 1997).

Assortativity refers to the tendency of organizations to connect on the basis of their similarity or dissimilarity expressed in terms of degree (Snijders et al., 2010) or intensity (Vu et al., 2017). Assortative networks are characterized by connections between nodes with a similar number of partners or levels of intensity. Dissortative networks, in contrast, are characterized by connections between nodes of dissimilar degree (Newman, 2002) or intensity (Lomi et al., 2014). Organizational studies have suggested that assortativity is a very heterogeneous attribute of networks. While interorganizational networks have usually been found to be assortative (Zhao et al., 2010), some recent studies have found evidence of assortative mixing (Stadtfeld et al., 2016) induced by organizational assimilation and differentiation.

In directed interorganizational systems, path-shortening behaviors include distinct forms of closure (Kogut and Walker, 2001; Uzzi, 1997). Tendencies toward closure generally refer to the propensity of organizations connected to the same partners to become directly connected through relational ties, or streams of relational events connecting sender and receiver organizations (Vu et al., 2017). Closure is ultimately produced by a variety of network antecedent configurations that can be empirically estimated. Examples of such antecedent network patterns include transitivity, generalized exchange, and distinct local forms of structural equivalence (Block, 2015; Lomi and Pallotti, 2013; Robins et al., 2009).

To understand how the presence of market uncertainty influences the macro-structure of roles in the European interbank market, this study focuses on the interplay between distinct classes of connectivity and closure micro-mechanisms. Regarding direct connectivity mechanisms, the current work distinguishes between *degree-* and *intensity-based* micro-mechanisms of preferential attachment, reciprocity, and trust. While degree-based mechanisms are simply computed by counting the number of relational events that have occurred among ordered pairs of sender and receivers nodes, the corresponding intensity-based counterparts take into account, for each sender, the unique number of its receivers. With the exception of transitive closure, this study conceives of closure mechanisms only in terms of their degree-based component with the ultimate purpose of facilitating their interpretation.

To properly capture the temporal dynamics behind role-switching, this study distinguishes between direct connectivity and closure mechanisms based on their short-term and long-term components, defined within suitable time frames. The empirical merit of doing so is twofold. In fact, as it has been extensively illustrated in Chapter 4, this distinction allows time-specific variations in micro-mechanisms to emerge and ultimately show that path-shortening micro-mechanisms do not operate uniformly over time – that is, they anticipate and eventually absorb market uncertainty along distinct exchange regimes and temporal frames because of their internal timing.

Identifying temporality and role-switching as key features of financial markets enables me to develop a set of testable hypotheses that illustrate how specific micro-mechanisms of partner selection may react to the emergence of market uncertainty. Reciprocity and transitive closure have been selected as representative micro-mechanisms on the basis of their capacity to represent the empirical regularities that are typically observed in interorganizational networks (Baum et al., 2003; Powell et al., 2005; Sorenson and Stuart, 2008).

5.3 Reciprocation and transitive closure under uncertainty

To clarify how basic micro-mechanisms, such as reciprocity and transitive closure, react to uncertainty, it is necessary to define them in the empirical context at hand. When temporality is the key element of the market micro-relational structure (see Chapter 4), the micro-mechanisms representative of such

micro-relational structure are ultimately defined by the exact timing associated with the time-ordered collection of transactions that emerge from it.

Reciprocity here refers to the alternate recurrence of buying and selling events between given pairs of financial organizations, and, clearly, its effects and meaning are not invariant to change in sequential ordering of the underlying exchange events that define it. Thus, from now on, in order to stress that reciprocity is actually a process capable of mirroring market relationships in light of the fine-grained history dependence behind any exchange event, I will use the term *reciprocation* in place of reciprocity. The correct identification of who is initiating action and *who* and *when* is reciprocating may matter greatly in the general understanding of role-switching as a strategy to face market uncertainty. In fact, on the one hand, the sequential ordering in social interaction provides important information about status differences and dominance relations (Chase, 1982; Gibson, 2005). On the other hand, such an ordering in social interaction often produces path-dependence (Gibson, 2011) in future sequences of transactions.

In the same fashion, transitive closure here refers to those sequences of transactions that connect two initially unconnected actors through the presence of a third common party. Also, in this case, information about the internal timing of transitive closure carries great empirical merit. For instance, the order and sequential constraints underlying the dynamics of transitive closure may help make sense of the development of population-level structures, such as hierarchies or embeddedness.

During the period of observation (2006-2015), the European interbank market has experienced several changes in the exchange regimes, all well documented by a series of studies primarily carried out by the European Central Bank (ECB) (Beaupain and Durré, 2008; Drudi et al., 2011, 2012). My idea is that such changes in exchange regimes correspond to new sources of market uncertainty, which in turn lead to a polarization of market roles and a reinforcement of existing credit relationships. On the one hand, adhering to the role of buyers or sellers of liquidity enables credit institutions to enhance their credibility on the market. On the other hand, adding existing relationships with existing partners is likely to result in stability and trust in relationships (Beckman et al., 2004; Podolny, 1994).

In the empirical case at hand, the turmoil period is characterized by the deepest level of uncertainty ever experienced in the European interbank market. In fact, the turmoil that occurred in August 2007 followed a period of stability and market functioning, during which there were no signs of a possible market crash and no doubts about the creditworthiness of market participants. When the Global Financial Crisis emerged, European banks were still struggling with the uncertainty emerged the summer before. To face the new stream of uncertainty produced by the collapse of Lehman Brothers in September 2008, along with a progressive reduction of volumes, banks also reduced the set of their effective trading counterparts. Finally, in addition to the turmoil phase, the Sovereign Debt crisis occurred in May 2010, following a period during which European banks had adapted to significant market changes and local fluctuations. Therefore, because of the fluctuating nature of market uncertainty experienced during the four different exchange regimes that define the whole period of observation, it is possible to isolate two distinct uncertainty reduction strategies. First, moving towards a polarization of market roles as an immediate reaction to new sources of market uncertainty. Second, moving towards role fluidity as a progressive adaptation to existing market uncertainty. As Fig. 5.1 suggests, the first strategy is reasonably carried out during the turmoil and SDC periods, while the second one is adopted during the proper emergence of the GFC phase. Overall, Fig. 5.1 reveals a positive correlation between the total number of lending contracts that a bank has hit and the unique number of its counterparts, thus showing that banks that typically

borrow from many lenders tend to be involved in more trading instances. However, this tendency varies considerably across the four exchange regimes.

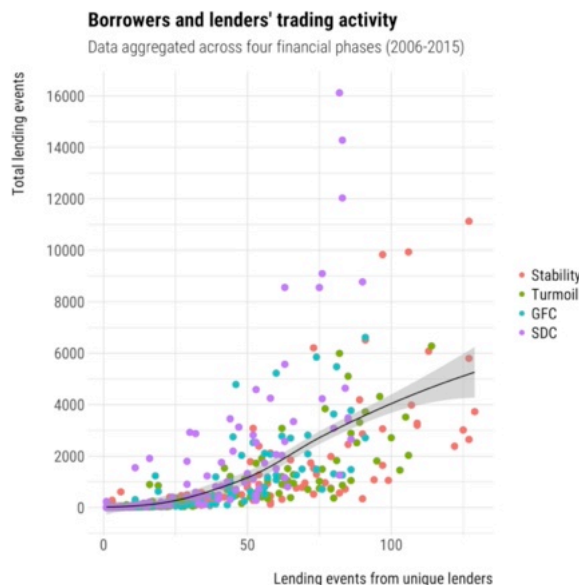


Fig. 5.1: Lenders and borrowers' trading activity across four financial phases

In particular, Fig. 5.1 shows that during the stability period, the number of transactions from unique lenders is usually greater than the same quantity measured within the subsequent phases, with some possible exceptions registered during the SDC period. Fig. 5.1 shows evidence in favor of role-polarization during the turmoil phase, with most of the banks concentrated in the bottom-right part of the plot. Evidence in favor of role-switching is observed during the GFC, with banks that are equally situated above and below the black line, which represents a smoothed version of the data. Finally, Fig. 5.1 suggests mixed evidence during the last period of observations, with some lenders that tend to reinforce their existing exchange relationships and others that tend to differentiate the panel of their possible borrowers.

Following the previous mix of theoretical claims and empirical evidence on how banks adjust their role under distinct sources of market uncertainty and temporal frames, I provide two sets of hypotheses about patterns of reciprocated exchange and transitive closure. I distinguish between degree- and intensity-based reciprocation by referring to the simple count of reciprocated transactions and the number of reciprocation weighted by the number of unique trading partners. While, in principle, the same distinction could also be applied to transitive closure, my analysis only considers degree-based transitive closure to provide a substantial interpretation of the underlying relational behavior. Finally, considering that the micro-relational structure of the European interbank market emerges from sequences of time-ordered transactions, I distinguish a short- and long-term component of reciprocation and transitive closure, thus following the path recently paved by Quintane et al. (2013) and Kitts et al. (2017). In line with this approach, I argue that if these micro-mechanisms unfold in the long term, they are an expression of the conventional understanding of social cohesion (Friedkin, 2004; Granovetter, 1973; Moreno and Jennings, 1937), while if they operate in the short term, they are indicative of adaptation to change. Overall, regularities in exchange relations emerge from both short- and long-term perspectives.

Hypothesis 1A [Degree-based, short-term reciprocation]

In the short run, the degree-based tendency toward reciprocation is positive and decreases as uncertainty arises. A decrease in reciprocity follows a contextual decrease in the propensity for role-switching, with credit institutions primarily acting as borrowers of overnight funds.

Hypothesis 1B [Degree-based, long-term reciprocation]

In the long run, the degree-based tendency toward reciprocation is positive and increases as uncertainty arises. An increase in reciprocity follows a contextual increase in the propensity for role-switching, with credit institutions acting both as borrowers and lenders of overnight funds.

Hypothesis 1C [Intensity-based, time-weighted reciprocation]

The tendency toward intensity-based reciprocation is positive and increases as uncertainty arises. An increase in reciprocity follows a contextual increase in the propensity for role-switching, with credit institutions acting both as borrowers and lenders of overnight funds within existing and well-established credit relationships.

Hypothesis 2A [Degree-based, short-term transitive closure]

In the short run, the degree-based tendency toward transitive closure is negative and increases as uncertainty arises. An increase in transitivity signals that banks are likely to entrench closer credit relationships with the trading partners of their borrowers.

Hypothesis 2B [Degree-based, long-term transitive closure]

In the long run, the degree-based tendency toward transitive closure increases as uncertainty arises. An increase in transitive closure signals that the tendency toward shared interaction with common third parties leads to the development of hierarchy logic.

Hypothesis 2C [Intensity-based, time-weighted transitive closure]

The tendency toward intensity-based transitive closure is negative and decreases as uncertainty arises. A decrease in the transitive closure corresponds to a contextual reinforcement of market roles within well-established credit relationships, aimed at managing urgent uncertainty.

5.4 Data and measurements

The time-stamped and relational dataset I analyze in the empirical section of this chapter encompasses all overnight transactions registered on the e-MID trading platform from 2006 to 2015. The data consists of 504,576 relational events corresponding to transactions between 202 European banks over 2,559 trading days. Information about their participation in the e-MID trading platform is updated at the beginning of each year, and this allows for the definition of an accurate risk set for the events.

The whole sample has been divided into four subsamples, each corresponding to a distinct exchange regime or financial phase as discussed in Chapter 2. A variable yet comparable number of transactions per financial phase has been registered during the period of observation, as documented by Tab. 5.1, which clearly shows how the trading activity on the European interbank market has progressively deteriorated after the turmoil period occurred in summer 2007. The daily number of transactions ranges from 570 during the stability phase to 19 during the SDC phase, with a global mean of 197.18 transactions per trading day throughout the entire observation period.

Between 2006 and 2015, almost all the transactions (96.5%) occurred among Italian banks with roles that are not equally distributed across the four financial phases, as Fig. 5.2. In fact, in general, most

Tab. 5.1: Summary statistics of the number of transactions stratified by phase

Phase	Number of transactions	Percentage of transactions	Min	Max	Median	Mean	Std.Dev.
Stability	141477	28.04	135	570	345.91	344	51.86
Turmoil	91349	18.10	82	497	325.09	328	59.50
GFC	89260	17.69	47	367	212.52	207	48.19
SDC	182490	36.17	19	301	125.94	114	47.06

of the *quoters* use the e-MID trading platform to borrow money, as the *sell* peaks corresponding to *aggressors* confirm. Globally, 27.02% and 72.98% of transactions refer to *buy* and *sell* labels, respectively¹.

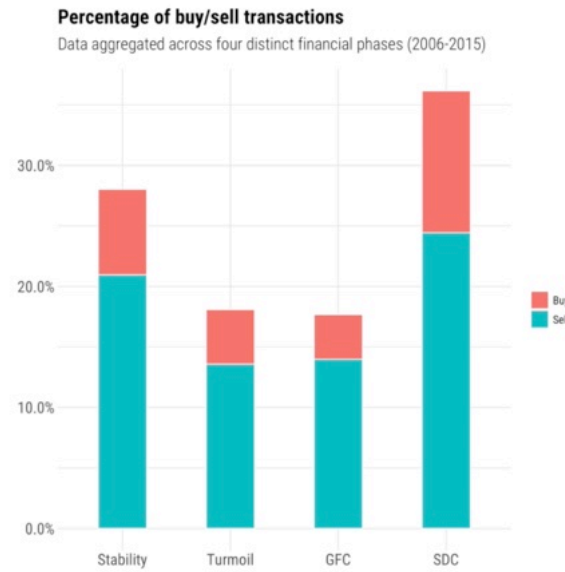


Fig. 5.2: Percentage of *buy* and *sell* transactions stratified by phase

An alternative and intuitive explanation of switching-role dynamics is offered by Tab. 5.2, which compares the proportion of transactions embedded in a network of reciprocated events and the exact proportions of transactions for which it exists a liquidity transfer in the opposite direction.

Along with the results presented in Fig. 5.1 and Fig. 5.2, the output reported in Tab. 5.2 confirms the general preference of credit institutions to enter into credit relationships as liquidity borrowers rather than liquidity providers. Regarding the effects of market uncertainty on reciprocation dynamics, empirical evidence in favor of role polarization appears to emerge during the turmoil phase, with a combined decrease in both reported measures compared to the stability period. A preference for role-switching begins to develop during the GFC period and, with mixed evidence, continues into the SDC phase.

¹See Chapter 2 for a detailed description of the trading mechanism adopted on the e-MID platform.

Tab. 5.2: Temporal dynamics of reciprocated transactions stratified by phase

Phase	Percentage of transactions embedded in a network of reciprocated exchange relations	Percentage of transactions actually reciprocated
Stability	43.59	10.96
Turmoil	30.33	7.76
GFC	28.10	6.36
SDC	43.44	9.84

5.5 Model

The model I introduce in this section provides an appropriate analytical framework for studying time-ordered sequences of relational events (Butts, 2008), namely a collection of exact times associated with the interactions between ordered pairs of buyers and sellers. Relational event models allow for the representation of the temporal dynamics of social relations at the same granularity level of the observed time-stamped data, with obvious advantages over other longitudinal models that aggregate temporal data into panel network data (Krivitsky and Handcock, 2014; Snijders et al., 2010). This class of models is nowadays quite rich and comprises multiple models rooted in distinct statistical traditions, such as event history analysis (Brandes et al., 2009; Butts, 2008), event-based actor-oriented models (Stadtfeld et al., 2017; Stadtfeld, 2012), and point-process models for social interaction data (Perry and Wolfe, 2013; Vu, 2012).

Inspired by the original work of Vu (2012), the model I use in this study has been recently adopted, in its original formulation, in other empirical studies by Amati et al. (2019), Lomi et al. (2014), and Vu et al. (2015, 2017). In the proposed version, the model is parametrized as suggested by Vu himself in the future directions of his dissertation (Vu, 2012, p. 110) and adapted to incorporate the distinction between degree- and intensity-based effects, as well as short- and long-term network effects. I apply this model to the sequence of 504,576 overnight transactions that occurred on the e-MID trading platform during the period 2006-2015, with the purpose of demonstrating that the emergence of market uncertainty alters the micro-mechanisms that reflect partner selection strategies. More in detail, as it has been extensively explained in Section 5.3, I am interested in evaluating the systematic variation of reciprocation and transitive closure over different time horizons, and across different exchange regimes.

In the next sections, I define the model based on the empirical setting depicted in 2 and analyzed in Section 5.4, in agreement with the orienting questions of the current study. However, a more general description of the model at hand can be obtained by considering banks as organizations and overnight liquidity transfers as relational events.

5.5.1 Model definition

The model assumes that banks join the network according to some stochastic process and create an edge every time a new transaction occurs. I indicate with t_e the time at which the transaction e occurred between the lender (sender) i and the borrower (receiver) j . Let $\mathcal{V} = \{1, \dots, n\}$ the set of banks in the network. Given an ordered pair of banks $(i, j) \in \mathcal{V}$, I indicate the collection of transactions involving the lender i and the receiver j with $E = \{(t_e, i, j), t_e \in \mathbb{R}^+, j \in \mathcal{R}_i(t_e), e \in \mathcal{V}\}$,

in which $\mathcal{R}_i(t_e)$ is the set of banks that are “at risk” of receiving a liquidity transfer from lender i at time t_e . Let

$$N_{ij}(t) = \# \{ \text{directed interactions } i \rightarrow j \text{ in time interval } [0, t] \},$$

and H_{t-} the history of all past trades right before time t .

Following Vu (2012), $N_{ij}(t)$ can be modeled by its *conditional intensity function* $\lambda_{ij}(t)$. Heuristically,

$$\lambda_{ij}(t) dt = \mathbb{P}\{\text{interaction } i \rightarrow j \text{ occurs in time interval } [t, t + dt]\}.$$

This means that the conditional intensity function corresponds to a conditional logit model, for example

$$\lambda_{ij}(t|H_{t-}) = \lambda_i(t) \cdot \exp[\beta' s(t, i, j)] \cdot \mathbb{1}\{j \in \mathcal{R}_i(t)\}, \quad (5.1)$$

where $s(t, i, j) \in \mathbb{R}^k$ is a vector of network statistics and $\beta \in \mathbb{R}^k$ is the vector of corresponding parameters. In contrast to other similar modeling approaches (Butts, 2008; Hunter et al., 2011; Perry and Wolfe, 2013; Vu et al., 2011), the term $\lambda_i(t)$ varies across lenders, allowing their heterogeneity to be absorbed into these baseline functions. Since banks that trade on the e-MID platform can be distinguished from one another only on the basis of their trading activity, this feature is of particular relevance in making up for the lack of bank covariates. However, the absence of banks’ nodal attributes might not be problematic. In fact, because of the short duration of overnight credit contracts, banks choose their trading counterparts on the basis of utilitarian motivations rather than speculative ones. This means that banks typically select their trading counterparts from the available trading partners at a given point in time.

5.5.2 Model specification

Network statistics for relational event models are defined as counts of local configurations referred to the micro-mechanisms that might have operated in a certain network. In contrast to other modeling approaches for network sequencing Butts (2008), Stadtfeld and Block (2017), and Stadtfeld (2012), the network statistics $s(t, i, j)$ included in Eq. 5.1 account for temporal dependencies among all the past transactions. Thus, their computation comprises a weight associated with each past event through a decay function $f(t, T_{ij}^e, \alpha)$, where t refers to the time at which the current event is taking place and T_{ij}^e refers to the time at which a transaction between lender i and borrower j has occurred in the past α days. In this empirical application, I assume that the temporal relevance of events decreases according to a power-law distribution, i.e. $f(t, T_{ij}^e, \alpha) = (t - T_{ij}^e)^{-\alpha}$ and set the decay parameter α equal to 5 days. As Amati et al. (2019) suggest, the parameter α can be optimally determined based on the data, but I set $\alpha = 5$ ex ante by referring to the five trading days in a week. Since the available dataset includes only overnight transactions, the one-week time horizon is the shortest available time span to evaluate some form of temporal dependence among transactions. Moreover, with the exclusion of *tomorrow-next* and *broken-dates* transactions – that refer to a lending scheme other than overnight transactions – one-week transactions are the most popular choice among European banks.

In Section 5.2, I introduced the micro-mechanisms that might guide changes in interorganizational networks. In this section, I introduce the network statistics related to these micro-mechanisms, which are defined based on the underlying relational event model.

Fig. ?? recalls how network statistics are built to take into account time-specific variations in network micro-mechanisms, while Tab. 5.3 provides their graphical representation and mathematical formulation. All the statistics listed in Tab. 5.3 have short- and long-term components. Given α equal to 5 days, short-term components of network statistics are computed within a time frame of 5 days, while long-term components are computed by setting an upper threshold to 30 days – the time frame in which the European banks usually have access to main refinancing operations (MROs) at the ECB. So, in a 30-day time window, the first 5 days refer to short-term statistics, while the next 25 relate to long-term statistics.

The first micro-mechanism I consider is *preferential attachment*, which refers to the tendency of credit institutions to select or be selected as trading partners. It is represented by a total of four degree and intensity-based statistics, all incorporating a temporal component. The *out-degree* and *out-intensity* statistics model lending banks' activity, while *in-degree* and *in-intensity* statistics model borrowing banks' popularity. Both the *out-degree* and *out-intensity* statistics are defined as functions of the out-degree of lender i , which is the number of i 's borrowers. On the one hand, because of the stratified-lender-intensity function, the out-degree is computed by summing the transactions over those banks that borrow overnight liquidity from lender i . This statistic has short- and long-term components that capture the temporal dependence among transactions. On the other hand, the out-intensity is computed as the weighted sum over the same liquidity borrowers, where weights account for both the number of transactions between the liquidity provider i and any of its counterparts, as well as the temporal relevance of trading events over a five-day period. In the same fashion, I characterize *in-degree* and *in-intensity* statistics.

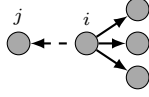
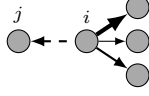
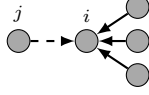
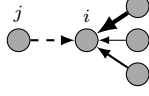
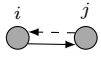
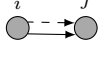
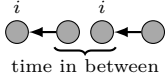
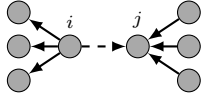
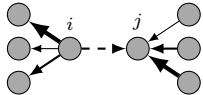
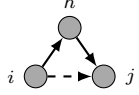
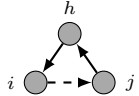
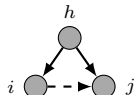
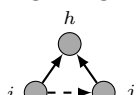

The second micro-mechanism that I introduce is *reciprocity*, which refers to the tendency of credit relations to be symmetric or, in other words, from banks' perspective, being each other's lenders and borrowers. The network statistic corresponding with reciprocity is *reciprocation*, which is computed as the sum of transactions from j to i , based on the existence of previous transactions from bank i to bank j . Degree-based reciprocation is characterized by short- and long-term components, while intensity-based reciprocation is defined by a time-weighted statistic in order to avoid possible collinearity issues.

The third micro-mechanism that I consider is *inertia*, which relates to the tendency of ties to persist over time. When inertia emerges from sequences of time-ordered transactions, it refers to the propensity of transactions to replicate themselves in the same direction they have occurred in the past. The corresponding network statistic is *trust*, which counts the number of transactions between an ordered pair of banks (i, j) weighted by their time relevance according to the usual degree- and intensity-based weighting scheme.

When inertia is paired with reciprocity, it allows for a comprehensive interpretation of reciprocation, which usually emerges after the development of trust – that is, after the observation of multiple transactions in the same direction at different time lags. Fig. 5.3 depicts two hypothetical patterns of repeated transactions that might lead, eventually, to the development of stable and mutual credit relationships. Even if I do not expect that all repeated transactions lead to reciprocal relationships, the prevalence of long-term patterns of reciprocal interaction is sustained by a series of repeated transactions that convey information about banks' creditworthiness.

The fourth micro-mechanism is *assortativity*, which refers to the tendency of banks to establish credit relationships based on the degree and intensity of similarity and dissimilarity in their relationships. In the empirical illustration, assortativity is modeled by *assortativity by degree* and *assortativity*

Tab. 5.3: Network statistics and their corresponding micro-mechanisms

Micro-mechanism	Network Statistic	Representation	Formula
Preferential attachment	Out-degree		$\sum_{j \neq i} \mathbb{1} [N_{ij}(t) > 0]$
	Out-intensity		$\frac{\sum_{j \neq i} \sum_{e=1}^{N_{ij}(t)} f(t, T_{ij}^e, \alpha)}{\sum_{j \neq i} \mathbb{1} [N_{ij}(t) > 0]}$
	In-degree		$\sum_{k \neq j} \mathbb{1} [N_{kj}(t) > 0]$
	In-intensity		$\frac{\sum_{k \neq j} \sum_{e=1}^{N_{kj}(t)} f(t, T_{kj}^e, \alpha)}{\sum_{k \neq j} \mathbb{1} [N_{kj}(t) > 0]}$
Reciprocity	Reciprocation		$\sum_{e=1}^{N_{ij}(t^-)} f(t, T_{ij}^e, \alpha)$
Inertia	Trust		$\sum_{e=1}^{N_{ij}(t^-)} f(t, T_{ij}^e, \alpha)$
	Recent receiving		$t - \max_{e \in E} t_e$
Assortativity	Assortativity by degree		$\text{out-degree}(t, i) \times \text{in-degree}(t, j)$
	Assortativity by intensity		$\text{out-intensity}(t, i) \times \text{in-intensity}(t, j)$
Closure	Transitive closure		$\sum_{h \neq i, j} g(w(t, i, h), w(t, h, j))$
	Cyclic closure		$\sum_{h \neq i, j} g(w(t, h, i), w(t, j, h))$
	Shared borrowers		$\sum_{h \neq i, j} g(w(t, h, i), w(t, h, j))$
	Shared lenders		$\sum_{h \neq i, j} g(w(t, i, h), w(t, j, h))$
	Matching		$\mathbb{1} [c(t, i) = c(t, j)]$

Note: $f(t, T_{ij}^e, \alpha) = (t - T_{ij}^e)^{-\alpha}$ and $w(t, i, h) = \sum_{e=1}^{N_{ih}(t^-)} f(t, T_{ih}^e, \alpha)$

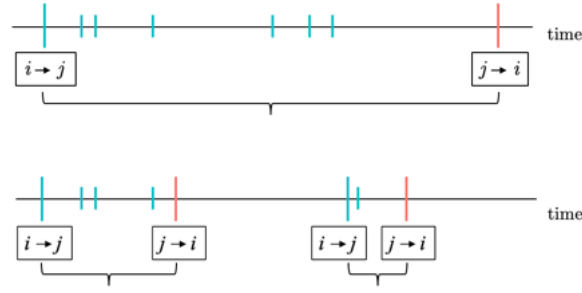


Fig. 5.3: Reciprocity as an outcome of trusted credit relationships

by *intensity* computed by referring to their short-term, long-term, and time-weighted components. Assortativity statistics are defined as interactions between out-degree and in-degree, and in-degree and in-intensity. Assortativity measures indicate whether there is a correlation between the out-degree of the liquidity provider and the in-degree of the liquidity borrower, and the out-intensity of the liquidity provider and the in-intensity of the liquidity borrower, respectively.

The last micro-mechanism of interest is closure, which relates to the tendency to establish credit relationships with the partners of our partners. In the empirical case at hand, I define several statistics to indicate how banks separated by one intermediary tend to become directly involved in a liquidity transfer. The *transitive closure* statistic refers to the likelihood of observing a transaction from i to j given the presence of a common third party h , acting as i 's borrower and j 's lender of overnight funds. As it has been extensively discussed in 4, this statistic is computed as a function of the number of two-paths, from i to h and from h to j , that ultimately are closed by a transaction from i to j . The *cyclic closure* statistic is defined in a similar fashion, but with two paths ordered differently, from j to h and from h to i . The statistic *shared borrowers* refers to the likelihood of a transaction from i to j given that they both receive overnight funds from h . Accordingly, the statistic *shared lenders* sees the connection between i and j more likely to occur in case they both lend liquidity to h . All the closure statistics, with the exception of transitive closure, are computed by considering their degree-based, short- and long-term specification. Even if, in principle, it is possible to define also their intensity-based specification, in practice, for ease of interpretation, it is preferable to consider only their degree-based specifications.

Finally, I control for homophily with respect to the nationality of the two credit institutions involved in the transfer of liquidity. So, I defined a *country-match* binary variable taking the value one if banks have the same country of origin and zero otherwise.

5.5.3 Model estimation and interpretation

Since β in Eq. 5.1 is the vector of parameters of a conditional logit model, it can be estimated by maximizing the likelihood

$$L(\beta) = \prod_{e \in E} \frac{\exp[\beta' s(t_e, i_e, j_e)]}{\prod_{h \in R_i(t_e)} \exp[\beta' s(t_e, i_e, h)]}. \quad (5.2)$$

Following Vu et al. (2011), the estimation procedure is done by generating a case-control data set of network statistics nested in the event times – that is, a data set in which the cases are the statistics (t_e, i_e, j_e) , while controls are (t_e, i_e, h) , with $h \neq j_e$. The outcome variable “transfer of overnight funds” takes value 1 for cases and 0 for controls, while the explanatory variables are the statistics

(t_e, i_e, j_e) and (t_e, i_e, h) . A suitable number of controls is sampled on the basis of Lerner and Lomi (2019). The stratified-by-sender approach $\lambda_i(t)$ helps to reduce the computational complexity and increase the efficiency of the sampling scheme. However, sender effects cannot be estimated.

The likelihood is maximized by using the same estimation algorithm employed to estimate conditional logistic regression models (Vu et al., 2017), and standard errors of the parameter estimates are obtained by computing the inverse of the Hessian matrix.

Even if the adopted relational event model is defined in terms of a conditional logit model, interpreting parameter estimates is not straightforward. In fact, because of the correlation among network statistics, quantities of interest like odds ratios can only be interpreted heuristically, rather than substantially. Therefore, when discussing the results, I will provide an interpretation of the parameter estimates based on their significance and sign. Positive values of parameter estimates reveal an increase in the likelihood of observing the corresponding micro-mechanism. A significant and positive value for reciprocation, for instance, provides evidence that banks tend to reciprocate with partners they have borrowed from. Similarly, a significant and positive value for transitive closure may be interpreted as evidence that banks prefer to lend liquidity to partners of their partners.

5.6 Results

To investigate how new sources of market uncertainty influence the temporal dynamics of partner selection strategies on the European interbank market, I estimated separate models for the cases and controls associated with each exchange regime and then compared the parameter estimates across the four phases. In so doing, events and non-events datasets are not treated as independent of one another, since the number of banks “at risk” in each phase is computed by taking into account the whole history of transactions stratified by exchange regimes. The models presented in this section encompass both direct connectivity and closure effects. The computation of network statistics is based on a time window of 30 days and an α equal to 5 days. Degree-based, short-term statistics are computed by considering the transactions that occurred in the first 5 days, while their long-term counterparts are computed by referring to the transactions that occurred in the next 25 days – that is, from day 6 to day 30. The same model computes intensity-based statistics by assigning an exponential decay ($\alpha = 0.5$) to all of the transactions that happened in the same week.

In principle, a comparison across exchange regimes can be done by comparing the magnitude and the confidence intervals of parameter estimates. However, when using logit and probit models, issues related to the presence of unobserved heterogeneity among groups (Allison, 1999; Mood, 2010) might arise. Even if some techniques exist for comparing parameter estimates of generalized linear models across groups, there is no consensus (Mood, 2010) on which practice is the most appropriate. Moreover, the validity of available methods might be questioned by the existence of correlation among network statistics, which can be very high in some cases. For all these reasons, I rely on signs and intensities of parameter estimates to describe time-specific variations in the micro-mechanisms that guide partner selection strategies. However, I draw conclusions about differences across exchange regimes by relying on the significance of parameter estimates.

Tab. 5.4 guides the interpretation of parameter estimates by listing, on the basis of previous studies on interorganizational networks, the expected signs of network statistics associated with the micro-mechanisms of interest and their interpretation.

Tab. 5.4: Network statistics and their interpretation

Network statistic	Expected sign	Interpretation
Out-degree	+	A positive estimate of the out-degree coefficient may be considered as evidence that lenders with a higher number of established target borrowers are more likely to send events.
Out-intensity	+	A positive effect of out-intensity effect may be taken as evidence that banks with high lending propensity in the past tend to lend more in the future.
In-degree	+	A positive effect of in-degree provides evidence for preferential attachment. So, banks with a larger number of lender tend to receive more transfers in the future.
In-intensity	+	A positive estimate of in-intensity is also expected to support evidence of preferential attachment. So, banks currently receiving a large number of transfers are more likely to be selected as borrowers for future transfers.
Reciprocation	+	A positive effect of reciprocation may be taken as evidence that borrowing banks tend to reciprocate lenders they have received transfers from.
Trust	+	A positive effect of trust can be interpreted as the tendency of lenders to prefer existing borrowers for future transfers.
Recent receiving	−	A negative coefficient associated with recent receiving implies that banks recently chosen as target partners are more likely to be selected in the future.
Assortativity by degree	−	A negative coefficient provides evidence for preferential relations. So, banks borrowing from many lenders are less likely to lend to popular borrowers. It is evidence of preferential relations.
Assortativity by intensity	−	A negative effect of assortativity by intensity implies that banks with high sending intensity are more likely to lend to banks with low borrowing intensity.
Transitive closure	+	A positive estimate of the coefficient may be interpreted as evidence that banks prefer to lend liquidity to partners of their partners.
Cyclic closure	−	A negative effect of cyclic closure and the presence of a positive transitive closure effect, implies a hierarchical clustered collaboration structure.
Shared partners	−	Negative effects of these statistics imply an unbalanced structure in the liquidity transfer network. In other words, banks are less likely to collaborate with each other if they share the same sending or receiving partners.

As Tab. 5.5 shows, with negligible exceptions, almost all of the parameter estimates are statistically significant. Interestingly, not all the network statistics exhibit signs consistent with the results of prior studies on interorganizational networks.

When dealing with preferential attachment statistics, the negative signs of the short-term, out-degree, and out-intensity parameters are unexpected. In contrast with long-term and positive out-degree statistics, a negative short-term out-degree statistic suggests that banks need more than a trading week to reinforce their activity as liquidity providers. Moreover, a time-weighted a strongly negative out-intensity effect can be taken as evidence that liquidity providers tend to constantly differentiate their portfolio of borrowers. The magnitude of parameter estimates confirms that liquidity providers actively reacted to the increased market uncertainty during the turmoil period by contracting the global volume of transactions. Their reaction is clearly evident over shorter temporal horizons, especially during financial periods marked by new sources of market uncertainty. Regular evidence of preferential attachment is revealed in the positive sign of in-degree and in-intensity statistics. Positive estimates of the in-degree and in-intensity parameters signal that liquidity providers tend to sell to banks that have been selected as trading partners by many others. In particular, an in-intensity parameter much greater than the corresponding in-degree seems to suggest that there is a restricted panel of banks that are likely to attract the resources available in the interbank market. In-degree parameters consistently increase across the four financial phases, in line with the cyclic nature of market uncertainty, thereby confirming that most active banks utilize the e-MID trading platform to request liquidity. The in-intensity parameter remains substantially unchanged across the turmoil and GFC phases, but considerably decreases right after the stability phase. When a new source of market uncertainty arises, lenders react by restricting their panel of borrowers and contextually choosing the most reliable trading counterparts, evaluated based on their activity.

When keeping the focus on reciprocity, the positive value of the reciprocation parameter suggests that reciprocating past transactions is more likely if those transactions are part of sequences of reciprocal liquidity transfers. However, it is the magnitude of parameters that reveals more insights about the dynamics of reciprocation across the global financial crisis. The degree-based component of reciprocity reveals that even a basic micro-mechanism, such as reciprocity, takes time to build but quickly dissolves as soon as market uncertainty increases. This finding is primarily suggested, on the one hand, by the sharp decrease of short-term reciprocity during the turmoil period and the contextual increase of the long-term components. On the other hand, the idea that banks require some time to incorporate uncertainty in their trading choices is revealed by the unquestionable convergence of short- and long-term components of degree-based reciprocation during the GFC phase. Interestingly, during the SDC phase, both the specifications of degree-based reciprocation adjust to the levels of reciprocation registered during the stability period, suggesting that the mechanism of role-switching remains effective in the presence of a diversified but trusted panel of trading counterparts, even in the event of new sources of market uncertainty arising. In fact, as the signs and statistical significance of the intensity-based reciprocation statistics reveal, when market uncertainty arose during the turmoil phase, liquidity providers initially avoided spontaneously offering liquidity on the e-MID trading platform, thereby reinforcing the trading relationships they had already established with borrowers in the past. Later on, once preferential credit relationships have been established, the role-switching mechanism started working again during the GFC period. Its intensity, however, decreases during the SDC period, maybe signaling a mix of the trading strategies carried out in the previous two periods. Altogether, these findings provide support for Hypotheses 1A and 1B. In the short term, within a five-day time frame, credit institutions prefer to request overnight liquidity to mitigate counterparty risk. In the long run, within a 30-day time frame, reciprocity increases and appears to operate as a

Tab. 5.5: Parameter estimates across four financial phases with threshold-time = 30 days and $\alpha = 5$ days

	Stability		Turnoil		GFC		SDC	
	$\hat{\beta}$	s.e.	$\hat{\beta}$	s.e.	$\hat{\beta}$	s.e.	$\hat{\beta}$	s.e.
<i>Preferential attachment</i>								
Out-degree (LT)	0.012***	(0.001)	0.003***	(0.001)	0.003***	(0.001)	0.000	(0.001)
Out-degree (ST)	-0.009***	(0.001)	-0.016***	(0.001)	-0.024***	(0.002)	-0.035***	(0.002)
Out-intensity (TW)	-0.423***	(0.011)	-0.209***	(0.010)	-0.324***	(0.014)	-0.094***	(0.006)
In-degree (LT)	0.017***	(0.001)	0.011***	(0.001)	0.008***	(0.001)	0.012***	(0.001)
In-degree (ST)	0.032***	(0.001)	0.037***	(0.002)	0.066***	(0.002)	0.071***	(0.002)
In-intensity (TW)	0.162***	(0.007)	0.111***	(0.008)	0.100***	(0.011)	0.115***	(0.007)
<i>Reciprocity</i>								
Reciprocation (D, LT)	0.002	(0.001)	0.005***	(0.001)	0.004***	(0.000)	0.001***	(0.000)
Reciprocation (D, ST)	0.028***	(0.002)	0.005**	(0.002)	0.006**	(0.002)	0.016***	(0.001)
Reciprocation (I, TW)	0.000	(0.000)	-0.002***	(0.001)	0.002*	(0.001)	0.000	(0.001)
<i>Inertia</i>								
Repetition (D, LT)	0.004***	(0.000)	0.004***	(0.000)	0.004***	(0.000)	0.002***	(0.000)
Repetition (D, ST)	0.025***	(0.001)	0.030***	(0.001)	0.035***	(0.001)	0.038***	(0.001)
Repetition (I, TW)	0.019***	(0.000)	0.017***	(0.001)	0.020***	(0.001)	0.010***	(0.001)
Last receiving (TW)	-0.119***	(0.003)	-0.132***	(0.005)	-0.037***	(0.002)	-0.045***	(0.002)
<i>Assortativity</i>								
Assortativity by degree (LT)	-0.001***	(0.000)	-0.001***	(0.000)	-0.001***	(0.000)	0.000***	(0.000)
Assortativity by degree (ST)	0.000***	(0.000)	0.000***	(0.000)	0.000*	(0.000)	-0.001***	(0.000)
Assortativity by intensity (TW)	-0.045***	(0.002)	-0.022***	(0.002)	-0.043***	(0.003)	-0.032***	(0.002)
<i>Closure</i>								
Transitive closure (D, LT)	0.094***	(0.003)	0.069***	(0.003)	0.061***	(0.003)	0.035***	(0.002)
Transitive closure (D, ST)	-0.003	(0.003)	0.002	(0.002)	-0.008***	(0.003)	0.003	(0.002)
Transitive closure (I, TW)	-0.014***	(0.001)	-0.019***	(0.001)	-0.007***	(0.001)	-0.007***	(0.000)
Cyclic closure (D, LT)	0.006**	(0.003)	0.001	(0.002)	0.000	(0.002)	0.002*	(0.001)
Cyclic closure (D, ST)	-0.030***	(0.003)	-0.019***	(0.003)	-0.017***	(0.004)	-0.024***	(0.003)
Shared borrowers (D, LT)	-0.019***	(0.003)	-0.013***	(0.002)	-0.005**	(0.002)	-0.006***	(0.002)
Shared borrowers (D, ST)	0.027***	(0.002)	0.017***	(0.002)	0.028***	(0.002)	0.025***	(0.002)
Shared lenders (D, LT)	0.017***	(0.002)	0.005***	(0.002)	0.002	(0.002)	-0.006***	(0.001)
Shared lenders (D, ST)	-0.015***	(0.003)	0.001	(0.002)	-0.003	(0.002)	0.011***	(0.002)
<i>Exogenous covariates</i>								
Country-match	1.359***	(0.033)	1.455***	(0.054)	1.564***	(0.076)	1.913***	(0.095)
Number of observations	424,431		274,047		267,780		547,359	
AIC	86,620.116		50,322.807		39,449.677		74,970.803	

Note: *p<0.1; **p<0.05; ***p<0.01

stabilizing mechanism, reinforcing existing credit relationships. Hypothesis 1C does not find empirical support. As soon as uncertainty emerges, both lenders and borrowers adhere to their roles in order to demonstrate their reliability to trading partners. Therefore, in more general terms, it is possible to argue that, when market uncertainty arises, symmetric credit relationships fully develop in the long run and especially with trusted trading partners. Such an effect may be related to the very notion of reciprocity that always invokes a response in time and, as such, defines the temporal structure of other norms of behavior. In this regard, I might speculate that differences in the time frames of reciprocity reflect, in a subtle way, the temporal dynamics of norms regarding solidarity, differences in status, or hierarchy.

Further insights on the dynamics of reciprocated exchange can be drawn by looking at parameters describing inertia in transactions. While extant research has recognized that the persistence of ties among organizations often supports the formation of new ties (Gulati and Gargiulo, 1999), based on trusted relationships, what has been missing so far is the recognition that repeated ties prelude to more complex structures of dependence among social actors. In this empirical context, for instance, high and positive levels of repeated transactions across the entire observation period, paired with high values of in-intensity and strongly negative values of last-receiving statistics, suggest that transactions are more likely to flow to recently receiving borrowers, especially in the context of preferential relationships. Such evidence provides much deeper understanding of the dynamics of reciprocation that are only apparently characterized as symmetric relationships. In fact, a reciprocated transaction usually occurs when borrowers have already established creditworthiness in their lenders' eyes, which typically happens after numerous close liquidity transfers, often concentrated within short time spans. Drawing upon the earlier body of qualitative (Hannan, 1998; Kitts, 2009; Kuwabara and Sheldon, 2012) and empirical work (Kitts et al., 2017) that recognizes the temporal dynamics of reciprocity in organizations, my work shows that the micro-mechanism of reciprocation plays out differently over time because it is ultimately driven by the temporal development of repeated transactions.

Assortativity mechanisms vary across financial phases. On the one hand, in the short run, there is no substantial evidence of degree-based assortativity, with the possible exception of the SDC phase, in which the corresponding parameter turns negative and increases in magnitude. On the other hand, degree-based assortativity operates in the long run with a positive sign in all the financial phases, except the last one. These results suggest that it takes at least 30 trading days to observe a connection between the most active banks on both sides of the market interface. In contrast to degree-based, long-term assortativity, intensity-based assortativity is negative and much stronger in terms of magnitude. These results indicate that the most active borrowers receive overnight funds from a small and select panel of preferred lenders, thereby confirming that within preferential relationships, roles tend to become crystallized. Moreover, it is worth noting that intensity-based assortativity decreases in financial periods when a new source of uncertainty arises, that is, during the turmoil and SDC phases. This tendency aligns with the reasoning that liquidity providers carefully select the *sell* quotes from potential borrowers. Ultimately, as the negative parameter for recent receiving suggests, the most desirable borrowers are those who are active over short time spans.

The parameter estimates related to the transitive closure provide evidence of different tendencies in the short and long run. In stark contrast to Hypothesis 2A, degree-based transitive closure seems not to operate in the short term, with the partial exception of the GFC period, thus confirming the general principle that the more actors are involved in the exchange, the more time it is required to activate the micro-mechanism of interest. In this phase, the unusual combination of negative parameters for both transitive and cyclic closure reveals actors' preference for dyadic random relationships. In line with Hypothesis 2B, the long-term parameters associated with degree-based transitive closure are all

positive and strong in magnitude. In periods of stability, lenders clearly tend to trust their borrowers. However, in periods of increased uncertainty, even if statistically significant, the tendency toward transitivity appears to be lower in magnitude, probably because of the general contraction of trading activity in the European interbank market that occurred immediately after the market turmoil in August 2007. Finally, in line with the previous arguments about the dynamics of preferential credit relationships, intensity-based transitive closure fully satisfies Hypothesis 2C, thereby revealing that borrowers tend to demonstrate their creditworthiness in dyadic relationships and through short-term, repeated transactions.

In contrast to transitive closure, there is no evidence for degree-based, long-term cyclic closure. This micro-mechanism operates only in the short term, and its negative sign suggests that transactions on the e-MID trading platform do not appear to follow a logic of generalized exchange. Moreover, a negative cyclic closure reveals some insights on the dynamics of reciprocated events through the principle of indirect reciprocity (Nowak and Sigmund, 2005). Indeed, non-reciprocated transactions occur at lower rates when they are part of locally cyclic structures, as confirmed by the positive and negative parameters associated with inertia and recent receiving, respectively.

Interestingly, although there is no empirical support for the shared-lenders micro-mechanism, the corresponding shared-borrowers network configuration operates differently in the short and long term. On the one hand, the positive sign and strong magnitude of the parameters suggest that borrowers sharing the same lender are prone to exchanging overnight funds in the short term. This trading behavior suggests that sharing the same trading role with respect to a third party can positively contribute to developing creditworthiness in the eyes of a new potential lender. However, in the presence of market turmoils, this micro-mechanism decreases its intensity, as it would be reasonably expected. On the other hand, the negative sign corresponding with the long-term shared-borrowers micro-mechanisms reveals that, within longer time horizons, two borrowers compete to receive overnight funds from the same liquidity provider.

Altogether, the empirical results presented in this section reveal that the European interbank market is composed of dense clusters of banks that adjust the flow of their transactions in response to their peers' interactions. Banks that are linked by preferential credit relationships tend to stick to specific roles, especially when new sources of market uncertainty arise. Tendencies toward role polarization persist in the short term, even in the case of sporadic overnight fund exchanges, albeit with a lower intensity, as indicated by the degree-based parameters of reciprocation and inertia. Moreover, as it was discussed, both reciprocation and transitive closure appear as fundamental micro-mechanisms capable of shaping cohesion and trust among European banks (Friedkin, 2004; Granovetter, 1973; Moreno and Jennings, 1937). In particular, the strong evidence of multiple processes of triadic closure demonstrates the propensity of credit institutions to develop time-sensitive group trading norms (Burt, 1992), which extend beyond reciprocal interactions. While patterns of reciprocal exchange typically unfold within longer temporal frames as a product of repeated transactions in the same direction, closure mechanisms can be activated within longer temporal horizons. In short time frames, closure is typically activated with the aim of responding to contingent liquidity needs, while in longer temporal frames, it functions as a process representative of cohesiveness or embedded exchange.

Finally, Fig. 5.4–5.6 report the parameter estimates with the corresponding 95% confidence intervals for degree- and activity-based reciprocation, repetition, and transitive closure, respectively. Red bars suggest that the corresponding parameters are not significantly different from zero, while light-blue bars refer to parameters that are significantly different from zero.

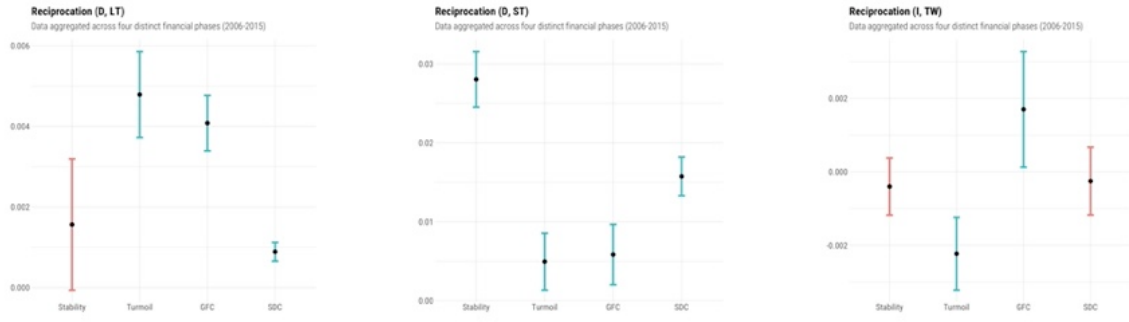


Fig. 5.4: Parameter values and corresponding 95% CI for degree- and intensity-based reciprocation

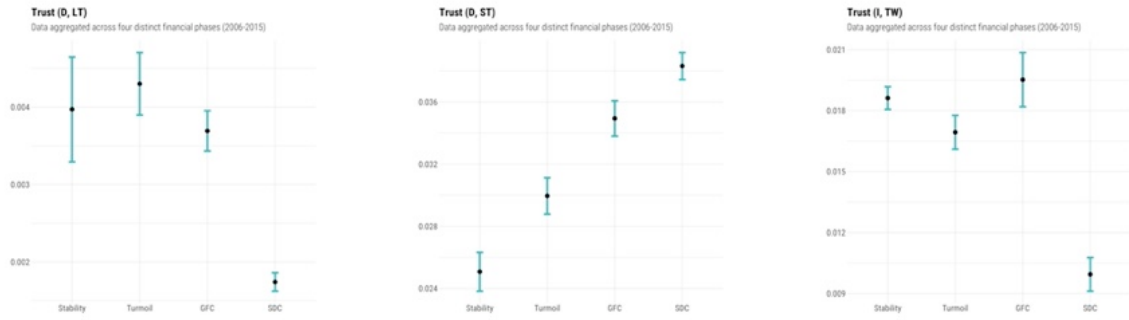


Fig. 5.5: Parameter values and corresponding 95% CI degree- and intensity-based repetition

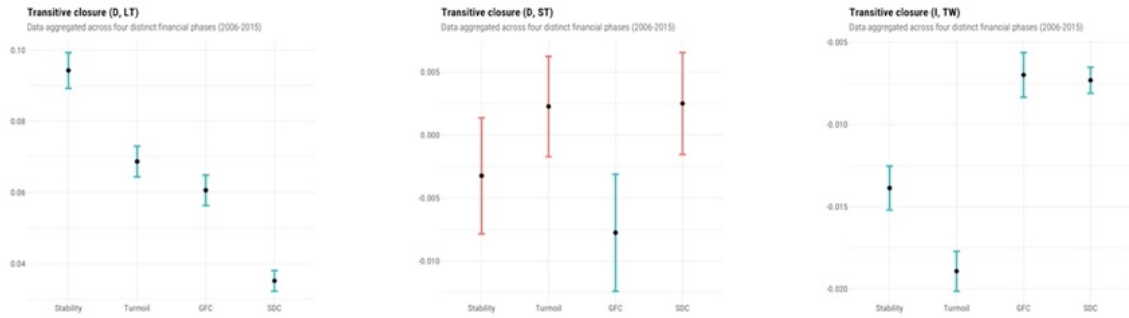


Fig. 5.6: Parameter values and corresponding 95% CI for degree- and intensity-based transitive closure

Not all the parameter estimates associated with reciprocation are significant. Yet, this result is not necessarily surprising when compared with parameter estimates for repetition. In this regard, Fig. 5.5 seems to suggest that reciprocated relations actually emerge in the context of repeated transactions, in patterns of exchange that resemble the pictorial description of reciprocation offered in Fig. 5.3. Parameter estimates associated with short-term transitive closure are significant only during the GFC. This result is not surprising, especially when paired with the *time to transitive closure* summary statistics discussed in Chapter 4. While transitive closure develops within time frames shorter than reciprocation, it is typically not observed before 5 trading days have passed. Overall, in line with the results that I obtained in Chapter 4 on the internal time distribution of reciprocation and transitive closure, I notice that the dynamics of reciprocation are more volatile in the short term, while transitive closure dynamics are better expressed in the short run. Altogether, these results support the existence of time-specific variations in network micro-mechanisms, as well

as the idea that distinct micro-mechanisms do not evolve in synchrony. This latter point, for instance, is particularly clear when looking at the short-term evolution of reciprocation and transitive closure across the phases. While reciprocation does not follow a clear path, transitive closure always decreases, thus signaling that European banks adapt to new sources of uncertainty by concentrating their trading activities within a trusted group of peers.

It may be reasonable to wonder if partner selection strategies adopted to address the emergence of new market uncertainties change within other time frames. As a robustness check, I reran the same model by extending the threshold time for computing network statistics to 90 days – that is, the time frame during which European banks have access to long-term refinancing operations.

Results presented in Tab. 5.6 do not exhibit significant changes with respect to those in Tab. 5.5. Then, the conclusions drawn in the current section are substantially valid within longer temporal horizons that regulate the trading activity on the e-MID platform. When comparing corresponding models through their Akaike Information Criteria, setting a threshold value of 30 days results in a better choice consistently, indicating that, regardless of market conditions, European banks primarily orient their trading activities to satisfy monthly reserve requirements imposed by the ECB.

5.7 Discussion and conclusions

The estimates reported in the previous section clearly show that European banks have reacted to the market uncertainty produced by the recent financial crises and accordingly have adjusted their partner selection strategies. Considerable research examining individual choices under uncertainty (Beckman et al., 2004; Podolny, 1994) is available, while comparatively less common is research investigating variations in collective choices (Corbo et al., 2016) at the field level. This is surprising because social mechanisms such as, for example, reciprocity, closure, and various forms of preferential attachment typically come into consideration as drivers of partner selection decisions in the context of interorganizational alliances (Gulati and Gargiulo, 1999).

While filling this gap, the current study reveals that uncertainty reduction strategies are inherent in the system of roles naturally entailed in the collection of micro-mechanisms that represent the micro-relational structure of financial markets. The main finding of my investigation is that the uncertainty that has recently plagued financial markets as a whole had a significant effect on the stability and fluidity of the market roles of buyers and sellers. This finding has immediate implications for the interpretation of reciprocation – the primary relational mechanism underlying role-switching – and other more complex relational mechanisms. Applicable when roles are not preassigned but rather acquired through interaction over time, the general norm of reciprocity emerges here with different nuances, defined by the temporal and domain-specific constraints. Regarding temporal constraints, the delay observed between two exchange threads of opposite direction is crucial for establishing roles across pairs of interacting banks. The observed delay, in fact, guarantees that the lending is done in the absence of a contractual obligation for a return. Domain-specific constraints refer to the value of the object of exchange, that is, overnight liquidity. When the exchanged good has an intrinsic value that is independent from the identities of the trading counterparts, reciprocation revolves more around the alternation of roles than around the quality of goods used to shape these roles. Overall, the mix of temporal and domain-specific constraints has the merit of indicating how much each side, as a buyer and a seller, must switch in order to develop a properly symmetric and beneficial exchange relationship. In more general terms, the emergence of new sources of market uncertainty does not prevent the formation of new connections, but instead makes actors more likely to include

Tab. 5.6: Parameter estimates across four financial phases with threshold-time = 90 days and $\alpha = 5$ days

	Stability		Turnoil		GFC		SDC	
	$\hat{\beta}$	s.e.	$\hat{\beta}$	s.e.	$\hat{\beta}$	s.e.	$\hat{\beta}$	s.e.
<i>Preferential attachment</i>								
Out-degree (LT)	0.006***	(0.001)	0.004***	(0.001)	0.002**	(0.001)	0.001	(0.001)
Out-degree (ST)	0.001	(0.001)	-0.005***	(0.001)	-0.005***	(0.002)	-0.021***	(0.001)
Out-intensity (TW)	-0.462***	(0.010)	-0.242***	(0.010)	-0.352***	(0.013)	-0.108***	(0.006)
In-degree (LT)	0.014***	(0.001)	0.008***	(0.001)	0.003**	(0.001)	0.008***	(0.001)
In-degree (ST)	0.030***	(0.002)	0.030***	(0.002)	0.053***	(0.002)	0.060***	(0.002)
In-intensity (TW)	0.214***	(0.007)	0.160***	(0.008)	0.148***	(0.010)	0.144***	(0.007)
<i>Reciprocity</i>								
Reciprocation (D, LT)	0.002**	(0.001)	0.006***	(0.001)	0.004***	(0.000)	0.001***	(0.000)
Reciprocation (D, ST)	0.029***	(0.002)	0.003	(0.002)	0.005**	(0.002)	0.015***	(0.001)
Reciprocation (I, TW)	-0.001	(0.000)	-0.002***	(0.001)	0.003***	(0.001)	0.000	(0.001)
<i>Inertia</i>								
Repetition (D, LT)	0.002***	(0.000)	0.003***	(0.000)	0.003***	(0.000)	0.002***	(0.000)
Repetition (D, ST)	0.028***	(0.001)	0.032***	(0.001)	0.037***	(0.001)	0.040***	(0.001)
Repetition (I, TW)	0.019***	(0.000)	0.017***	(0.001)	0.020***	(0.001)	0.010***	(0.001)
Last receiving (TW)	-0.124***	(0.003)	-0.148***	(0.005)	-0.044***	(0.002)	-0.049***	(0.002)
<i>Assortativity</i>								
Assortativity by degree (LT)	-0.001***	(0.000)	-0.001***	(0.000)	-0.001***	(0.000)	0.000***	(0.000)
Assortativity by degree (ST)	0.000	(0.000)	0.000**	(0.000)	0.000***	(0.000)	0.000***	(0.000)
Assortativity by intensity (TW)	-0.047***	(0.002)	-0.024***	(0.002)	-0.041***	(0.003)	-0.035***	(0.002)
<i>Closure</i>								
Transitive closure (D, LT)	0.101***	(0.003)	0.069***	(0.003)	0.062***	(0.003)	0.037***	(0.002)
Transitive closure (D, ST)	-0.014***	(0.003)	-0.005	(0.003)	-0.008**	(0.003)	-0.015***	(0.003)
Transitive closure (I, TW)	-0.010***	(0.001)	-0.015***	(0.001)	-0.006***	(0.001)	-0.006***	(0.000)
Cyclic closure (D, LT)	0.010***	(0.003)	0.002	(0.002)	0.000	(0.002)	0.002	(0.001)
Cyclic closure (D, ST)	-0.033***	(0.003)	-0.020***	(0.003)	-0.018***	(0.004)	-0.024***	(0.003)
Shared borrowers (D, LT)	-0.011***	(0.003)	-0.012***	(0.002)	-0.005**	(0.002)	-0.007***	(0.002)
Shared borrowers (D, ST)	0.020***	(0.002)	0.012***	(0.002)	0.022***	(0.002)	0.026***	(0.002)
Shared lenders (D, LT)	0.014***	(0.002)	0.004**	(0.002)	0.002	(0.002)	-0.005***	(0.001)
Shared lenders (D, ST)	-0.014***	(0.003)	0.002	(0.002)	-0.008***	(0.002)	0.006***	(0.002)
<i>Exogenous covariates</i>								
Country-match	1.342***	(0.033)	1.415***	(0.054)	1.511***	(0.076)	1.851***	(0.095)
Number of observations	424,431		274,047		267,780		547,359	
AIC	88,347.116		52,322.823		41,906.314		77,067.644	

Note: *p<0.1; **p<0.05; ***p<0.01

new exchange threads in meaningful microstructures of exchange, thus reducing the prevalence of random ties.

Finally, in accordance with the preliminary analysis on *network times* presented in Chapter 4, my results confirm that role-switching behaviors operate across distinct exchange regimes and in short- and long-term temporal frames. Differentiating between diverse temporal frames and measuring organizational processes at the same granularity they are evaluated and monitored is crucial to gaining a proper understanding of network dynamics. In this regard, despite the obvious limitations of a single empirical case, the results discussed in this study provide strong empirical evidence of a contingent and time-dependent network structure.

Bibliography

- [AB08] Franklin Allen and Ana Babus. “Networks in finance”. In: (2008) (cit. on p. 10).
- [Abb83] Andrew Abbott. “Sequences of social events: Concepts and methods for the analysis of order in social processes”. In: *Historical Methods: A Journal of Quantitative and Interdisciplinary History* 16.4 (1983), pp. 129–147 (cit. on p. 43).
- [Abb90] Andrew Abbott. “A primer on sequence methods”. In: *Organization science* 1.4 (1990), pp. 375–392 (cit. on pp. 7, 42).
- [Abb95] Andrew Abbott. “Sequence analysis: New methods for old ideas”. In: *Annual Review of Sociology* 21.1 (1995), pp. 93–113 (cit. on pp. 8, 42).
- [Abo01] Mitchel Abolafia. *Making markets: Opportunism and restraint on Wall Street*. Harvard University Press, 2001 (cit. on p. 3).
- [Aff12] Massimiliano Affinito. “Do interbank customer relationships exist? And how did they function in the crisis? Learning from Italy”. In: *Journal of Banking & Finance* 36.12 (2012), pp. 3163–3184 (cit. on pp. 11, 17).
- [Ake70] George Akerlof. “The market for lemons: Qualitative uncertainty and the market mechanismv”. In: *Quarterly Journal of Economics* 84.3 (1970) (cit. on p. 55).
- [All+09] Franklin Allen, Ana Babus, Paul R. Kleindorfer, and Yoram Wind. *The network challenge: strategy, profit, and risk in an interlinked world*. 2009 (cit. on pp. 2, 6).
- [All99] Paul D. Allison. “Comparing logit and probit coefficients across groups”. In: *Sociological Methods & Research* 28.2 (1999), pp. 186–208 (cit. on p. 67).
- [ALM19] Viviana Amati, Alessandro Lomi, and Daniele Mascia. “Some days are better than others: Examining time-specific variation in the structuring of interorganizational relations”. In: *Social Networks* 57 (2019), pp. 18–33 (cit. on pp. 40–42, 52, 62, 63).
- [Anc+01] Deborah G. Ancona, Paul S. Goodman, Barbara S. Lawrence, and Michael L. Tushman. “Time: A new research lens”. In: *Academy of Management Review* 26.4 (2001), pp. 645–663 (cit. on p. 42).
- [ANP11] Paolo Angelini, Andrea Nobili, and Cristina Picillo. “The interbank market after August 2007: what has changed, and why?”. In: *Journal of Money, Credit and Banking* 43.5 (2011), pp. 923–958 (cit. on pp. 15, 29).
- [AS11] Viral V. Acharya and David Skeie. “A model of liquidity hoarding and term premia in inter-bank markets”. In: *Journal of Monetary Economics* 58.5 (2011), pp. 436–447 (cit. on p. 32).
- [Asp11] Patrik Aspers. “Markets, evaluations and rankings”. In: *Historical Social Research/Historische Sozialforschung* (2011), pp. 19–33 (cit. on pp. 18, 20, 52, 55).
- [Bak84] Wayne E. Baker. “The social structure of a national securities market”. In: *American Journal of Sociology* 89.4 (1984), pp. 775–811 (cit. on pp. 4, 17, 28, 41, 56).
- [Bak90] Wayne E. Baker. “Market networks and corporate behavior”. In: *American Journal of Sociology* 96.3 (1990), pp. 589–625 (cit. on pp. 3, 17, 56).

- [Bar+17a] Marco Bardoscia, Stefano Battiston, Fabio Caccioli, and Guido Caldarelli. “Pathways towards instability in financial networks”. In: *Nature Communications* 8 (2017), p. 14416 (cit. on p. 2).
- [Bar+17b] Francesco Bartolucci, Francesca Chiaromonte, Prabhani Kuruppumullage Don, and Bruce G. Lindsay. “Composite likelihood inference in a discrete latent variable model for two-way “clustering-by-segmentation” problems”. In: *Journal of Computational and Graphical Statistics* 26.2 (2017), pp. 388–402 (cit. on p. 26).
- [Bat+10] Stefano Battiston, James B. Glattfelder, Diego Garlaschelli, Fabrizio Lillo, and Guido Caldarelli. “The structure of financial networks”. In: *Network Science*. Springer, 2010, pp. 131–163 (cit. on pp. 2, 6, 10).
- [BC06] Kenneth A. Bollen and Patrick J. Curran. *Latent curve models: A structural equation perspective*. Vol. 467. John Wiley & Sons, 2006 (cit. on p. 21).
- [BD08] Renaud Beaupain and Alain Durré. *The interday and intraday patterns of the overnight market: Evidence from an electronic platform*. Tech. rep. ECB Working Paper, 2008 (cit. on pp. 6, 27–29, 58).
- [BD11] Renaud Beaupain and Alain Durré. “Inferring trading dynamics for an OTC market: The case of the euro area overnight money market”. In: *Quantitative Finance* 11.9 (2011), pp. 1285–1295 (cit. on pp. 27, 29).
- [Ber12] Jose Berrospide. “Liquidity hoarding and the financial crisis: An empirical evaluation”. In: *Retrieved March 10* (2012), p. 2013 (cit. on p. 32).
- [BF16] Falk Bräuning and Falko Fecht. “Relationship lending in the interbank market and the price of liquidity”. In: *Review of Finance* 21.1 (2016), pp. 33–75 (cit. on p. 17).
- [BHP04] Christine M. Beckman, Pamela R. Haunschild, and Damon J. Phillips. “Friends or strangers? Firm-specific uncertainty, market uncertainty, and network partner selection”. In: *Organization Science* 15.3 (2004), pp. 259–275 (cit. on pp. 54, 56, 58, 74).
- [Bla64] Peter Blau. “Power and exchange in social life”. In: *New York: J Wiley & Sons* 352 (1964) (cit. on p. 20).
- [Blo15] Per Block. “Reciprocity, transitivity, and the mysterious three-cycle”. In: *Social Networks* 40 (2015), pp. 163–173 (cit. on p. 57).
- [Blo+18] Per Block, Johan Koskinen, James Hollway, Christian Steglich, and Christoph Stadtfeld. “Change we can believe in: Comparing longitudinal network models on consistency, interpretability and predictive power”. In: *Social Networks* 52 (2018), pp. 180–191 (cit. on p. 40).
- [BLS09] Ulrik Brandes, Jürgen Lerner, and Tom A.B. Snijders. “Networks evolving step by step: Statistical analysis of dyadic event data”. In: *Social Network Analysis and Mining, 2009. ASONAM’09. International Conference on Advances in*. IEEE, 2009, pp. 200–205 (cit. on pp. 6, 62).
- [BM08] Angelo Baglioni and Andrea Monticini. “The intraday price of money: Evidence from the e-MID interbank market”. In: *Journal of Money, Credit and Banking* 40.7 (2008), pp. 1533–1540 (cit. on p. 13).
- [Bos+04] Michael Boss, Helmut Elsinger, Martin Summer, and Stefan Thurner. “Network topology of the interbank market”. In: *Quantitative Finance* 4.6 (2004), pp. 677–684 (cit. on p. 11).
- [BP03] Jushan Bai and Pierre Perron. “Computation and analysis of multiple structural change models”. In: *Journal of Applied Econometrics* 18.1 (2003), pp. 1–22 (cit. on p. 16).
- [Bra18] Laurence Brandenberger. “Trading favors – Examining the temporal dynamics of reciprocity in congressional collaborations using relational event models”. In: *Social Networks* 54 (2018), pp. 238–253 (cit. on p. 20).
- [BSR03] Joel A.C. Baum, Andrew V. Shipilov, and Tim J. Rowley. “Where do small worlds come from?” In: *Industrial and Corporate Change* 12.4 (2003), pp. 697–725 (cit. on pp. 56, 57).

- [BT18] N. Brunsson and A. Tyllström. “When sellers organize markets: Dilemmas and strategies in markets for professional service markets”. In: *Organizing and re-organizing markets*. 2018 (cit. on p. 55).
- [Bur83] Ronald S. Burt. *Corporate profits and cooptation: Networks of market constraints and directorate ties in the American economy*. Academic Press, New York, 1983 (cit. on p. 54).
- [Bur92] Ronald S. Burt. *Structural holes: The social structure of competition*. Harvard University Press, 1992 (cit. on pp. 43, 55, 72).
- [But08] Carter T. Butts. “A relational event framework for social action”. In: *Sociological Methodology* 38.1 (2008), pp. 155–200 (cit. on pp. 6, 7, 18, 22, 40, 42–44, 62, 63).
- [But09] Carter T. Butts. “Revisiting the foundations of network analysis”. In: *Science* 325.5939 (2009), pp. 414–416 (cit. on pp. 42, 43).
- [Car89] Dennis W. Carlton. “The theory and the facts of how markets clear: is industrial organization valuable for understanding macroeconomics?” In: *Handbook of Industrial Organization* 1 (1989), pp. 909–946 (cit. on p. 3).
- [CCF16] Leonardo Corbo, Raffaele Corrado, and Simone Ferriani. “A new order of things: Network mechanisms of field evolution in the aftermath of an exogenous shock”. In: *Organization Studies* 37.3 (2016), pp. 323–348 (cit. on pp. 18, 74).
- [CCPZ15] Ethan Cohen-Cole, Eleonora Patacchini, and Yves Zenou. “Static and dynamic networks in interbank markets”. In: *Network Science* 3.1 (2015), pp. 98–123 (cit. on pp. 4, 41).
- [CGM09] João F. Cocco, Francisco J. Gomes, and Nuno C. Martins. “Lending relationships in the inter-bank market”. In: *Journal of Financial Intermediation* 18.1 (2009), pp. 24–48 (cit. on pp. 10, 40).
- [CH+92] John M Chambers, Trevor J Hastie, et al. *Statistical models in S*. Vol. 251. Wadsworth & Brooks/Cole Advanced Books & Software Pacific Grove, CA, 1992 (cit. on p. 24).
- [Cha82] Ivan D. Chase. “Behavioral sequences during dominance hierarchy formation in chickens”. In: *Science* 216.4544 (1982), pp. 439–440 (cit. on pp. 7, 42, 43, 58).
- [CHL91] John L. Campbell, J. Rogers Hollingsworth, and Leon N. Lindberg. *Governance of the American economy*. Vol. 5. Cambridge University Press, 1991 (cit. on p. 2).
- [Col88] James S. Coleman. “Social capital in the creation of human capital”. In: *American Journal of Sociology* 94 (1988), S95–S120 (cit. on pp. 43, 55, 56).
- [DD14] Daniele Durante and David B. Dunson. “Nonparametric Bayes dynamic modelling of relational data”. In: *Biometrika* 101.4 (2014), pp. 883–898 (cit. on p. 22).
- [DDM11] Francesco Drudi, Alain Durré, and Francesco P. Mongelli. “The ECB and the implications of the sovereign debt crisis”. In: *Conference on “Who will Provide the Next Financial Model?”* 2011 (cit. on p. 58).
- [DDM12] Francesco Drudi, Alain Durré, and Francesco P. Mongelli. “The interplay of economic reforms and monetary policy: the case of the Eurozone”. In: *Journal of Common Market Studies* 50.6 (2012), pp. 881–898 (cit. on pp. 14–16, 29, 33, 51, 55, 58).
- [DG84] Peter J. Diggle and Richard J. Gratton. “Monte Carlo methods of inference for implicit statistical models”. In: *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 46.2 (1984), pp. 193–212 (cit. on p. 38).
- [DMIC06] Giulia De Masi, Giulia Iori, and Guido Caldarelli. “Fitness model for the Italian interbank money market”. In: *Physical Review E* 74.6 (2006), p. 066112 (cit. on p. 11).
- [DMO17] Ritabrata Dutta, Antonietta Mira, and Jukka-Pekka Onnela. “Bayesian Inference of Network Epidemics”. In: *arXiv preprint arXiv:1709.08862* (2017) (cit. on p. 38).

- [DYB03] Gerald F. Davis, Mina Yoo, and Wayne E. Baker. “The small world of the American corporate elite, 1982-2001”. In: *Strategic Organization* 1.3 (2003), pp. 301–326 (cit. on p. 56).
- [Dye96] Jeffrey H. Dyer. “Specialized supplier networks as a source of competitive advantage: Evidence from the auto industry”. In: *Strategic Management Journal* 17.4 (1996), pp. 271–291 (cit. on p. 55).
- [EGJ14] Matthew Elliott, Benjamin Golub, and Matthew O. Jackson. “Financial networks and contagion”. In: *The American Economic Review* 104.10 (2014), pp. 3115–3153 (cit. on p. 2).
- [Eme72] Richard M. Emerson. “Exchange theory, part II: Exchange relations and networks”. In: *Sociological Theories in Progress* 2 (1972), pp. 58–87 (cit. on p. 52).
- [Eme76] Richard M. Emerson. “Social exchange theory”. In: *Annual Review of Sociology* 2.1 (1976), pp. 335–362 (cit. on p. 20).
- [ET86] Bradley Efron and Robert Tibshirani. “Bootstrap methods for standard errors, confidence intervals, and other measures of statistical accuracy”. In: *Statistical Science* (1986), pp. 54–75 (cit. on p. 26).
- [ET97] Bradley Efron and Robert Tibshirani. “Improvements on cross-validation: the 632+ bootstrap method”. In: *Journal of the American Statistical Association* 92.438 (1997), pp. 548–560 (cit. on p. 26).
- [FFL13] Karl Finger, Daniel Fricke, and Thomas Lux. “Network analysis of the e-MID overnight money market: the informational value of different aggregation levels for intrinsic dynamic processes”. In: *Computational Management Science* 10.2-3 (2013), pp. 187–211 (cit. on pp. 11, 27, 28, 52).
- [FG00] Ernst Fehr and Simon Gächter. “Fairness and retaliation: The economics of reciprocity”. In: *Journal of Economic Perspectives* 14.3 (2000), pp. 159–181 (cit. on p. 42).
- [FL15] Daniel Fricke and Thomas Lux. “Core-periphery structure in the overnight money market: evidence from the e-MID trading platform”. In: *Computational Economics* 45.3 (2015), pp. 359–395 (cit. on pp. 11, 17, 27, 46, 52).
- [FL17] Karl Finger and Thomas Lux. “Network formation in the interbank money market: An application of the actor-oriented model”. In: *Social Networks* 48 (2017), pp. 237–249 (cit. on pp. 11, 27).
- [FMW85] Stephen E. Fienberg, Michael M. Meyer, and Stanley Wasserman. “Statistical analysis of multiple sociometric relations”. In: *Journal of the American Statistical Association* 80.389 (1985), pp. 51–67 (cit. on p. 22).
- [Fos61] George M. Foster. “The dyadic contract: a model for the social structure of a Mexican peasant village”. In: *American Anthropologist* 63.6 (1961), pp. 1173–1192 (cit. on p. 5).
- [FRF87] Linton C. Freeman, A. Kimball Romney, and Sue C. Freeman. “Cognitive structure and informant accuracy”. In: *American Anthropologist* 89.2 (1987), pp. 310–325 (cit. on p. 56).
- [Fri04] Noah E. Friedkin. “Social cohesion”. In: *Annual Review of Sociology* 30 (2004), pp. 409–425 (cit. on pp. 20, 42, 43, 55, 59, 72).
- [Fru+16] Juan Carlos Frutos, Carlos Garcia-de Andoain, Florian Heider, and Patrick Papsdorf. *Stressed interbank markets: Evidence from the European financial and sovereign debt crisis*. Tech. rep. ECB, 2016 (cit. on p. 21).
- [FS86] Ove Frank and David Strauss. “Markov graphs”. In: *Journal of the American Statistical Association* 81.395 (1986), pp. 832–842 (cit. on p. 22).
- [FW81] Stephen E. Fienberg and Stanley Wasserman. “Categorical data analysis of single sociometric relations”. In: *Sociological Methodology* 12 (1981), pp. 156–192 (cit. on p. 21).
- [Gab+13] Giampaolo Gabbi, Guido Germano, Vasilis Hatzopoulos, Giulia Iori, and Mauro Politi. “Market Microstructure, Banks’ Behaviour, and Interbank Spreads”. In: (2013) (cit. on pp. 13, 14).

- [GG99] Ranjay Gulati and Martin Gargiulo. “Where do interorganizational networks come from?” In: *American Journal of Sociology* 104.5 (1999), pp. 1439–1493 (cit. on pp. 71, 74).
- [Gib03] David R. Gibson. “Participation shifts: Order and differentiation in group conversation”. In: *Social Forces* 81.4 (2003), pp. 1335–1380 (cit. on pp. 41, 43).
- [Gib05] David R. Gibson. “Taking turns and talking ties: Networks and conversational interaction”. In: *American Journal of Sociology* 110.6 (2005), pp. 1561–1597 (cit. on pp. 43, 58).
- [Gib08] David R. Gibson. “How the outside gets in: Modeling conversational permeation”. In: *Annual Review of Sociology* 34 (2008), pp. 359–384 (cit. on p. 43).
- [Gib11] David R. Gibson. “Avoiding catastrophe: The interactional production of possibility during the Cuban missile crisis”. In: *American Journal of Sociology* 117.2 (2011), pp. 361–419 (cit. on pp. 43, 58).
- [GM11] Scott A. Golder and Michael W. Macy. “Diurnal and seasonal mood vary with work, sleep, and daylength across diverse cultures”. In: *Science* 333.6051 (2011), pp. 1878–1881 (cit. on p. 40).
- [GN08] Ranjay Gulati and Jack A. Nickerson. “Interorganizational trust, governance choice, and exchange performance”. In: *Organization Science* 19.5 (2008), pp. 688–708 (cit. on p. 56).
- [Gou60] Alvin W. Gouldner. “The norm of reciprocity: A preliminary statement”. In: *American Sociological Review* (1960), pp. 161–178 (cit. on pp. 5, 20).
- [Gra73] Mark Granovetter. “The strength of weak ties”. In: *American Journal of Sociology* (1973), pp. 1360–1380 (cit. on pp. 42, 43, 55, 59, 72).
- [Gra82] Mark Granovetter. “The strength of weak ties: A network theory revisited”. In: *Sociological Theory* (1982), pp. 201–233 (cit. on pp. 43, 55).
- [Gra85] Mark Granovetter. “Economic action and social structure: The problem of embeddedness”. In: *American Journal of Sociology* 91.3 (1985), pp. 481–510 (cit. on p. 11).
- [Gra92] Mark Granovetter. “Economic institutions as social constructions: a framework for analysis”. In: *Acta Sociologica* 35.1 (1992), pp. 3–11 (cit. on p. 11).
- [GWH07] Scott A. Golder, Dennis M. Wilkinson, and Bernardo A. Huberman. “Rhythms of social interaction: Messaging within a massive online network”. In: *Communities and Technologies*. Springer, 2007, pp. 41–66 (cit. on p. 44).
- [Han98] Michael T. Hannan. “Rethinking age dependence in organizational mortality: Logical formalizations”. In: *American Journal of Sociology* 104.1 (1998), pp. 126–164 (cit. on p. 71).
- [Hat+15] Vasilis Hatzopoulos, Giulia Iori, Rosario N. Mantegna, Salvatore Micciché, and Michele Tumminello. “Quantifying preferential trading in the e-MID interbank market”. In: *Quantitative Finance* 15.4 (2015), pp. 693–710 (cit. on pp. 11, 14, 16, 27).
- [HD97] David R. Heise and Alex Durig. “A frame for organizational actions and macroactions”. In: *Journal of Mathematical Sociology* 22.2 (1997), pp. 95–123 (cit. on p. 4).
- [HFX+10] Steve Hanneke, Wenjie Fu, Eric P. Xing, et al. “Discrete temporal models of social networks”. In: *Electronic Journal of Statistics* 4 (2010), pp. 585–605 (cit. on p. 22).
- [HL81] Paul W. Holland and Samuel Leinhardt. “An exponential family of probability distributions for directed graphs”. In: *Journal of the American Statistical Association* 76.373 (1981), pp. 33–50 (cit. on pp. 7, 21, 22, 38).
- [HLL83] Paul W. Holland, Kathryn Blackmond Laskey, and Samuel Leinhardt. “Stochastic blockmodels: First steps”. In: *Social Networks* 5.2 (1983), pp. 109–137 (cit. on p. 21).
- [Hun+11] David Hunter, Padhraic Smyth, Duy Q. Vu, and Arthur U. Asuncion. “Dynamic egocentric models for citation networks”. In: *Proceedings of the 28th International Conference on Machine Learning (ICML-11)*. 2011, pp. 857–864 (cit. on pp. 22, 63).

- [IM09] Carmela Iazzetta and Michele Manna. *The topology of the interbank market: developments in Italy since 1990*. Tech. rep. Bank of Italy Working Paper, 2009 (cit. on pp. 11, 46, 52).
- [Ior+07] Giulia Iori, Roberto Reno, Giulia De Masi, and Guido Caldarelli. “Trading strategies in the Italian interbank market”. In: *Physica A: Statistical Mechanics and its Applications* 376 (2007), pp. 467–479 (cit. on p. 11).
- [Ior+08] Giulia Iori, Giulia De Masi, Ovidiu V. Precup, Giampaolo Gabbi, and Guido Caldarelli. “A network analysis of the Italian overnight money market”. In: *Journal of Economic Dynamics and Control* 32.1 (2008), pp. 259–278 (cit. on p. 11).
- [Ior+15] Giulia Iori, Rosario N. Mantegna, Luca Marotta, et al. “Networked relationships in the e-MID Interbank market: A trading model with memory”. In: *Journal of Economic Dynamics and Control* 50 (2015), pp. 98–116 (cit. on pp. 11, 27, 40).
- [IR00] Paul Ingram and Peter W. Roberts. “Friendships among competitors in the Sydney hotel industry”. In: *American Journal of Sociology* 106.2 (2000), pp. 387–423 (cit. on p. 43).
- [KH14] Pavel N. Krivitsky and Mark S. Handcock. “A separable model for dynamic networks”. In: *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 76.1 (2014), pp. 29–46 (cit. on pp. 22, 62).
- [Kit09] James A. Kitts. “Paradise lost: age-dependent mortality of American communes, 1609–1965”. In: *Social Forces* 87.3 (2009), pp. 1193–1222 (cit. on p. 71).
- [Kit+17] James A. Kitts, Alessandro Lomi, Daniele Mascia, Francesca Pallotti, and Eric Quintane. “Investigating the temporal dynamics of interorganizational reciprocity: Patient exchange among Italian hospitals”. In: *American Journal of Sociology* (2017) (cit. on pp. 18, 20, 40–43, 46, 59, 71).
- [KM58] Edward L. Kaplan and Paul Meier. “Nonparametric estimation from incomplete observations”. In: *Journal of the American Statistical Association* 53.282 (1958), pp. 457–481 (cit. on p. 48).
- [KS12] Ko Kuwabara and Oliver Sheldon. “Temporal dynamics of social exchange and the development of solidarity: “testing the waters” versus “taking a leap of faith””. In: *Social Forces* 91.1 (2012), pp. 253–273 (cit. on p. 71).
- [KW01] Bruce Kogut and Gordon Walker. “The small world of Germany and the durability of national networks”. In: *American Sociological Review* (2001), pp. 317–335 (cit. on pp. 56, 57).
- [Lei88] Eric M. Leifer. “Interaction preludes to role setting: Exploratory local action”. In: *American Sociological Review* (1988), pp. 865–878 (cit. on pp. 4, 41, 53, 55).
- [LGM78] Edward O. Laumann, Joseph Galaskiewicz, and Peter V. Marsden. “Community structure as interorganizational linkages”. In: *Annual Review of Sociology* 4.1 (1978), pp. 455–484 (cit. on pp. 4, 6).
- [Lie97] John Lie. “Sociology of markets”. In: *Annual Review of Sociology* 23.1 (1997), pp. 341–360 (cit. on p. 2).
- [Lin02] Charles E. Lindblom. *The market system: What it is, how it works, and what to make of it*. Yale University Press, 2002 (cit. on pp. 2, 3).
- [Lin88] Bruce G. Lindsay. “Composite likelihood methods”. In: *Contemporary Mathematics* 80.1 (1988), pp. 221–239 (cit. on p. 22).
- [LL19] Jürgen Lerner and Alessandro Lomi. “The network structure of successful collaboration in Wikipedia”. In: *Proceedings of the 52nd Hawaii International Conference on System Sciences*. 2019 (cit. on pp. 40, 67).
- [LM82] Edward O. Laumann and Peter V. Marsden. “Microstructural analysis in interorganizational systems”. In: *Social Networks* 4.4 (1982), pp. 329–348 (cit. on pp. 4, 6, 40, 56).

- [Lom+14] Alessandro Lomi, Daniele Mascia, Duy Q. Vu, et al. “Quality of care and interhospital collaboration: a study of patient transfers in Italy”. In: *Medical Care* 52.5 (2014), p. 407 (cit. on pp. 57, 62).
- [LP06] Alessandro Lomi and Philippa Pattison. “Manufacturing relations: An empirical study of the organization of production across multiple networks”. In: *Organization Science* 17.3 (2006), pp. 313–332 (cit. on p. 55).
- [LP13] Alessandro Lomi and Francesca Pallotti. *How to close a hole: Exploring alternative closure mechanisms in interorganizational networks*. 2013 (cit. on pp. 54, 57).
- [LXH17] Kevin H. Lee, Lingzhou Xue, and David R. Hunter. “Model-based clustering of time-evolving networks through temporal exponential-family random graph models”. In: *arXiv preprint arXiv:1712.07325* (2017) (cit. on p. 22).
- [Man06] N. Gregory Mankiw. *Principles of macroeconomics*. Cengage Learning, 2006 (cit. on p. 2).
- [MCWG+95] Andreu Mas-Colell, Michael Dennis Whinston, Jerry R. Green, et al. *Microeconomic theory*. Vol. 1. Oxford University Press, 1995 (cit. on p. 2).
- [Mey82] Alan D. Meyer. “Adapting to environmental jolts”. In: *Administrative Science Quarterly* (1982), pp. 515–537 (cit. on p. 55).
- [Mil+78] Raymond E. Miles, Charles C. Snow, Alan D. Meyer, and Henry J. Coleman Jr. “Organizational strategy, structure, and process”. In: *Academy of Management Review* 3.3 (1978), pp. 546–562 (cit. on p. 54).
- [Mis11] Ann Mische. “Relational sociology, culture, and agency”. In: *The Sage Handbook of Social Network Analysis* (2011), pp. 80–97 (cit. on p. 43).
- [MJ37] Jacob L. Moreno and Helen H. Jennings. “Statistics of social configurations”. In: *Sociometry* (1937), pp. 342–374 (cit. on pp. 59, 72).
- [MO79] James G. March and Johan P. Olsen. *Ambiguity and choice in organizations*. Universitetsforlaget, 1979 (cit. on p. 54).
- [Moo10] Carina Mood. “Logistic regression: Why we cannot do what we think we can do, and what we can do about it”. In: *European Sociological Review* 26.1 (2010), pp. 67–82 (cit. on p. 67).
- [MPT03] Linda D. Molm, Gretchen Peterson, and Nobuyuki Takahashi. “In the eye of the beholder: Procedural justice in social exchange”. In: *American Sociological Review* (2003), pp. 128–152 (cit. on p. 43).
- [MSC07] Linda D. Molm, David R. Schaefer, and Jessica L. Collett. “The value of reciprocity”. In: *Social Psychology Quarterly* 70 (2007), pp. 199–217 (cit. on p. 20).
- [MWM12] Linda D. Molm, Monica M. Whitham, and David Melamed. “Forms of exchange and integrative bonds: Effects of history and embeddedness”. In: *American Sociological Review* 77.1 (2012), pp. 141–165 (cit. on p. 20).
- [New01] Mark E.J. Newman. “Clustering and preferential attachment in growing networks”. In: *Physical Review E* 64.2 (2001), p. 025102 (cit. on p. 56).
- [New02] Mark E.J. Newman. “Assortative mixing in networks”. In: *Physical Review Letters* 89.20 (2002), p. 208701 (cit. on p. 57).
- [New10] Mark Newman. *Networks: An introduction*. Oxford University Press, 2010 (cit. on p. 2).
- [NS05] Martin A. Nowak and Karl Sigmund. “Evolution of indirect reciprocity”. In: *Nature* 437.7063 (2005), p. 1291 (cit. on pp. 43, 72).
- [Pod94] Joel M. Podolny. “Market uncertainty and the social character of economic exchange”. In: *Administrative Science Quarterly* (1994), pp. 458–483 (cit. on pp. 54–56, 58, 74).

- [Pow+05] Walter W. Powell, Douglas R. White, Kenneth W. Koput, and Jason Owen-Smith. “Network dynamics and field evolution: The growth of interorganizational collaboration in the life sciences”. In: *American Journal of Sociology* 110.4 (2005), pp. 1132–1205 (cit. on pp. 7, 52, 55–57).
- [Pow90] Walter W. Powell. “Neither market nor hierarchy”. In: *Research in Organizational Behavior* 12 (1990), pp. 295–336 (cit. on p. 20).
- [PS78] Jeffrey Pfeffer and Gerald R. Salancik. *The external control of organizations: A resource dependence perspective*. Harper and Row, New York, 1978 (cit. on p. 54).
- [PW13] Patrick O. Perry and Patrick J. Wolfe. “Point process modelling for directed interaction networks”. In: *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 75.5 (2013), pp. 821–849 (cit. on pp. 22, 40, 42, 43, 62, 63).
- [Qui+13] Eric Quintane, Philippa Pattison, Garry Robins, and Joeri M. Mol. “Short-and long-term stability in organizational networks: Temporal structures of project teams”. In: *Social Networks* 35.4 (2013), pp. 528–540 (cit. on pp. 18, 20, 40–43, 59).
- [Rob+07] Garry Robins, Philippa Pattison, Yuval Kalish, and Dean Lusher. “An introduction to exponential random graph (p^*) models for social networks”. In: *Social Networks* 29.2 (2007), pp. 173–191 (cit. on p. 22).
- [Rou+13] Tarik Roukny, Hugues Bersini, Hugues Pirotte, Guido Caldarelli, and Stefano Battiston. “Default cascades in complex networks: Topology and systemic risk”. In: *Scientific Reports* 3 (2013) (cit. on p. 2).
- [RP08] Lori Rosenkopf and Giovanna Padula. “Investigating the microstructure of network evolution: Alliance formation in the mobile communications industry”. In: *Organization Science* 19.5 (2008), pp. 669–687 (cit. on pp. 7, 56).
- [RPW09] Garry Robins, Philippa Pattison, and Peng Wang. “Closure, connectivity and degree distributions: Exponential random graph (p^*) models for directed social networks”. In: *Social Networks* 31.2 (2009), pp. 105–117 (cit. on p. 57).
- [RRP10] Olaf N. Rank, Garry Robins, and Philippa Pattison. “Structural logic of intraorganizational networks”. In: *Organization Science* 21.3 (2010), pp. 745–764 (cit. on p. 43).
- [RSU10] Mark T. Rivera, Sara B. Soderstrom, and Brian Uzzi. “Dynamics of dyads in social networks: Assortative, relational, and proximity mechanisms”. In: *Annual Review of Sociology* 36 (2010), pp. 91–115 (cit. on pp. 42, 55, 56).
- [Rub14] Paul H. Rubin. “Emporiophobia (fear of markets): Cooperation or competition?” In: *Southern Economic Journal* 80.4 (2014), pp. 875–889 (cit. on p. 5).
- [Rub+84] Donald B. Rubin et al. “Bayesianly justifiable and relevant frequency calculations for the applied statistician”. In: *The Annals of Statistics* 12.4 (1984), pp. 1151–1172 (cit. on p. 38).
- [SB17] Christoph Stadtfeld and Per Block. “Interactions, actors, and time: Dynamic network actor models for relational events”. In: *Sociological Science* 4 (2017), pp. 318–352 (cit. on pp. 41, 63).
- [SBS10] Tom A.B. Snijders, Gerhard G. Van de Bunt, and Christian Steglich. “Introduction to stochastic actor-based models for network dynamics”. In: *Social Networks* 32.1 (2010), pp. 44–60 (cit. on pp. 6, 42, 43, 57, 62).
- [SD03] Wesley D. Sine and Robert J. David. “Environmental jolts, institutional change, and the creation of entrepreneurial opportunity in the US electric power industry”. In: *Research Policy* 32.2 (2003), pp. 185–207 (cit. on p. 54).
- [SHB17] Christoph Stadtfeld, James Hollway, and Per Block. “Dynamic network actor models: Investigating coordination ties through time”. In: *Sociological Methodology* 47.1 (2017), pp. 1–40 (cit. on pp. 42, 62).

- [SI90] David Strauss and Michael Ikeda. “Pseudolikelihood estimation for social networks”. In: *Journal of the American statistical association* 85.409 (1990), pp. 204–212 (cit. on p. 22).
- [SM57] Herbert Simon and James March. *Administrative behavior and organizations*. New York: Free Press, 1957 (cit. on p. 54).
- [Smy00] Padhraic Smyth. “Model selection for probabilistic clustering using cross-validated likelihood”. In: *Statistics and Computing* 10.1 (2000), pp. 63–72 (cit. on p. 26).
- [Sni+06] Tom A.B. Snijders, Philippa Pattison, Garry Robins, and Mark S. Handcock. “New specifications for exponential random graph models”. In: *Sociological Methodology* 36.1 (2006), pp. 99–153 (cit. on p. 22).
- [Sni90] Tom A.B. Snijders. “Testing for change in a digraph at two time points”. In: *Social Networks* 12.4 (1990), pp. 359–373 (cit. on p. 43).
- [Sni96] Tom A.B. Snijders. “Stochastic actor-oriented models for network change”. In: *Journal of Mathematical Sociology* 21.1-2 (1996), pp. 149–172 (cit. on pp. 22, 43).
- [SS08] Olav Sorenson and Toby E. Stuart. “Bringing the context back in: Settings and the search for syndicate partners in venture capital investment networks”. In: *Administrative Science Quarterly* 53.2 (2008), pp. 266–294 (cit. on p. 57).
- [Sta12] Christoph Stadtfeld. *Events in social networks: A stochastic actor-oriented framework for dynamic event processes in social networks*. KIT Scientific Publishing, 2012 (cit. on pp. 40, 62, 63).
- [Sta+16] Christoph Stadtfeld, Daniele Mascia, Francesca Pallotti, and Alessandro Lomi. “Assimilation and differentiation: A multilevel perspective on organizational and network change”. In: *Social Networks* 44 (2016), pp. 363–374 (cit. on p. 57).
- [Stu98] Toby E. Stuart. “Network positions and propensities to collaborate: An investigation of strategic alliance formation in a high-technology industry”. In: *Administrative Science Quarterly* (1998), pp. 668–698 (cit. on p. 56).
- [SV06] David Stark and Balázs Vedres. “Social times of network spaces: Network sequences and foreign investment in Hungary”. In: *American Journal of Sociology* 111.5 (2006), pp. 1367–1411 (cit. on p. 44).
- [SVLG13] Tiziano Squartini, Iman Van Lelyveld, and Diego Garlaschelli. “Early-warning signals of topological collapse in interbank networks”. In: *Scientific Reports* 3 (2013), p. 3357 (cit. on p. 17).
- [SY10] Toby E. Stuart and Soojin Yim. “Board interlocks and the propensity to be targeted in private equity transactions”. In: *Journal of Financial Economics* 97.1 (2010), pp. 174–189 (cit. on p. 56).
- [Tav+97] Simon Tavaré, David J. Balding, Robert C. Griffiths, and Peter Donnelly. “Inferring coalescence times from DNA sequence data”. In: *Genetics* 145.2 (1997), pp. 505–518 (cit. on p. 38).
- [Tho67] James D. Thompson. *Organizations in action: Social science bases of administration*. New York: McGraw-Hill, 1967 (cit. on p. 54).
- [TIMR15] Asena Temizsoy, Giulia Iori, and Gabriel Montes-Rojas. “The role of bank relationships in the interbank market”. In: *Journal of Economic Dynamics and Control* 59 (2015), pp. 118–141 (cit. on pp. 14, 17).
- [TJS14] Qingjiu Tom Tao, Ruihua Joy Jiang, and Michael D. Santoro. “Expand or retrench? Alliance portfolio adaptation to environmental jolts”. In: *International Journal of Business Environment* 7.1 (2014), pp. 79–97 (cit. on p. 54).
- [Tum+11] Michele Tumminello, Salvatore Micciché, Fabrizio Lillo, Jyrki Piilo, and Rosario N. Mantegna. “Statistically validated networks in bipartite complex systems”. In: *PLOS One* 6.3 (2011), e17994 (cit. on p. 11).

- [Uzz96] Brian Uzzi. “The sources and consequences of embeddedness for the economic performance of organizations: The network effect”. In: *American Sociological Review* (1996), pp. 674–698 (cit. on pp. 20, 28, 43, 51, 55).
- [Uzz97] Brian Uzzi. “Social structure and competition in interfirm networks: The paradox of embeddedness”. In: *Administrative Science Quarterly* (1997), pp. 35–67 (cit. on pp. 3, 43, 51, 54–57).
- [Uzz99] Brian Uzzi. “Embeddedness in the making of financial capital: How social relations and networks benefit firms seeking financing”. In: *American Sociological Review* (1999), pp. 481–505 (cit. on p. 42).
- [Var92] Hal R. Varian. *Microeconomic analysis*. Norton&Company, 1992 (cit. on p. 2).
- [VDSZ04] Marijtje A.J. Van Duijn, Tom A.B. Snijders, and Bonne J.H. Zijlstra. “p2: a random effects model with covariates for directed graphs”. In: *Statistica Neerlandica* 58.2 (2004), pp. 234–254 (cit. on p. 22).
- [VPR15] Duy Q. Vu, Philippa Pattison, and Garry Robins. “Relational event models for social learning in MOOCs”. In: *Social Networks* 43 (2015), pp. 121–135 (cit. on p. 62).
- [VRF11] Cristiano Varin, Nancy Reid, and David Firth. “An overview of composite likelihood methods”. In: *Statistica Sinica* (2011), pp. 5–42 (cit. on p. 22).
- [Vri95] Nicolaas J. Vriend. “Self-organization of markets: An example of a computational approach”. In: *Computational Economics* 8.3 (1995), pp. 205–231 (cit. on p. 4).
- [Vu+11] Duy Q. Vu, David Hunter, Padhraic Smyth, and Arthur U. Asuncion. “Continuous-time regression models for longitudinal networks”. In: *Advances in Neural Information Processing Systems*. 2011, pp. 2492–2500 (cit. on pp. 22, 63, 66).
- [Vu12] Duy Q. Vu. “Statistical models and algorithms for large network analysis”. PhD thesis. Pennsylvania State University, 2012 (cit. on pp. 7, 62, 63).
- [Vu+17] Duy Q. Vu, Alessandro Lomi, Daniele Mascia, and Francesca Pallotti. “Relational event models for longitudinal network data with an application to interhospital patient transfers”. In: *Statistics in Medicine* 36.14 (2017), pp. 2265–2287 (cit. on pp. 42, 44, 56, 57, 62, 67).
- [Wan+09] Peng Wang, Ken Sharpe, Garry Robins, and Philippa Pattison. “Exponential random graph (p^*) models for affiliation networks”. In: *Social Networks* 31.1 (2009), pp. 12–25 (cit. on p. 22).
- [Was87] Stanley Wasserman. “Conformity of two sociometric relations”. In: *Psychometrika* 52.1 (1987), pp. 3–18 (cit. on p. 22).
- [Wei96] Karl E. Weick. “Drop your tools: An allegory for organizational studies”. In: *Administrative Science Quarterly* (1996), pp. 301–313 (cit. on p. 54).
- [WF94] Stanley Wasserman and Katherine Faust. *Social network analysis: Methods and applications*. Vol. 8. Cambridge University Press, 1994 (cit. on p. 20).
- [WG84] Stanley Wasserman and Joseph Galaskiewicz. “Some generalizations of p1: External constraints, interactions and non-binary relations”. In: *Social Networks* 6.2 (1984), pp. 177–192 (cit. on p. 22).
- [Whi70] Harrison C. White. *Chains of opportunity. System models of mobility in organizations*. Harvard University Press, 1970 (cit. on pp. 7, 42).
- [Whi81] Harrison C. White. “Where do markets come from?” In: *American Journal of Sociology* 87.3 (1981), pp. 517–547 (cit. on pp. 2, 17, 41, 56).
- [WI86] Stanley Wasserman and Dawn Iacobucci. “Statistical analysis of discrete relational data”. In: *British Journal of Mathematical and Statistical Psychology* 39.1 (1986), pp. 41–64 (cit. on p. 22).
- [WI88] Stanley Wasserman and Dawn Iacobucci. “Sequential social network data”. In: *Psychometrika* 53.2 (1988), pp. 261–282 (cit. on p. 22).

- [Wil75] Oliver E. Williamson. *Markets and hierarchies*. New York: Free Press, 1975 (cit. on p. 54).
- [Wil81] Oliver E. Williamson. “The economics of organization: The transaction cost approach”. In: *American Journal of Sociology* 87.3 (1981), pp. 548–577 (cit. on p. 54).
- [Wil85] Oliver E. Williamson. *The economic institutions of capitalism: Firms, markets, relational contracting*. New York: Free Press, 1985 (cit. on pp. 3, 4, 54).
- [Won87] George Y. Wong. “Bayesian models for directed graphs”. In: *Journal of the American Statistical Association* 82.397 (1987), pp. 140–148 (cit. on p. 22).
- [WP96] Stanley Wasserman and Philippa Pattison. “Logit models and logistic regressions for social networks: I. An introduction to Markov graphs and p^* ”. In: *Psychometrika* 61.3 (1996), pp. 401–425 (cit. on p. 22).
- [WW87] Yuchung J. Wang and George Y. Wong. “Stochastic blockmodels for directed graphs”. In: *Journal of the American Statistical Association* 82.397 (1987), pp. 8–19 (cit. on p. 21).
- [Zaw13] Adam Zawadowski. “Entangled financial systems”. In: *The Review of Financial Studies* 26.5 (2013), pp. 1291–1323 (cit. on pp. 2, 6, 10).
- [Zha+10] Kang Zhao, Louis-Marie Ngamassi, John Yen, Carleen Maitland, and Andrea Tapia. “Assortativity patterns in multi-dimensional inter-organizational networks: a case study of the humanitarian relief sector”. In: *International Conference on Social Computing, Behavioral Modeling, and Prediction*. Springer. 2010, pp. 265–272 (cit. on p. 57).

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