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A time to give and a time to receive: Role switching and generalized exchange in a financial market

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ABSTRACT

We study the effect of generalized exchange as a possible mechanism reproducing the flows of resources among participants in financial markets. In an analysis of on-line trading in a major European interbank market for liquidity, we find that generalized exchange is unlikely to affect sequences of short-term market transactions, but it emerges forcefully in the longer-term. This empirical result is consistent with our predictions that generalized exchange may be understood only with reference to the temporal micro-structure of transactions linking occupants of market roles ("buyers" and "sellers," in our case). We also find that generalized exchange does not affect larger market transactions in the shorter-term, and is unlikely to emerge in the longer-term. This result is consistent with our prediction that generalized exchange does not operate as a stabilizing mechanism for asymmetric market transactions when they involve higher levels of risk. The results of the study clarify how and when context-specific differences in time and value of transactions trigger (or inhibit) generic network mechanisms in decentralized systems of exchange like, for example, markets.

Any market is a social formation which decouples sellers from buyers exactly by turning the particular persons into occupants of roles [.]. Other varieties of such social formations are, for example, ritual prestation cycles of gifts. (White and Eccles, 1987, p.984)

1. Introduction

Not always interaction precedes role setting (Leifer, 1988). In the typical market, for example, the irreversibility of investments in specialized assets (Pindyck, 1990), and the time needed to acquire production experience (Cohen and Levinthal, 1994), lock "buyers" and "sellers" into relatively stable roles that make exchange possible – even when ecological rotation changes the occupants of those roles (Hannan and Freeman, 1977). In the short term, irreversible investments in specialized assets make the social structure of markets work as a set of exogenous constraints (Lomi et al., 2010). These constraints are so powerful and pervasive that they are typically taken for granted, rather than treated as problematic, in research on the sociology of markets (Burt, 1988; White, 1981b), and organizations (Hannan and Freeman, 1984).

Financial markets are different. In financial markets roles of "buyer" and "seller" are contingent to individual transactions. Buyers and sellers may switch roles at any time almost without cost, and – more meaningfully in a sociological sense – without incurring any significant social sanction or devaluation typically associated with unclear or ambiguous identities (Hannan, 2010). The emergence of dominant roles from sequences of transactions makes financial markets more similar to ecological systems where social positions are determined by path-dependent outcomes of interaction among participants (Chase et al., 2002; Lindquist and Chase, 2009; Chase and Lindquist, 2016). Calling attention on the fluidity of their role structure, Ahrne et al. (2015) label financial markets "switch-role markets."

Role setting in financial markets is shaped by interaction taking the form of sequences of time-ordered transactions where each participant may switch from "buyer" to "seller" (and back) almost at any time. Differences in patterns of exchange between financial and product markets are generally well understood (Knorr-Cetina, 2012; Knorr-Cetina and Preda, 2007; Aspers, 2011). Framing such differences in term of market roles is less common and, we argue, particularly useful as it reveals a natural connection between sociological theories of exchange and large samples of observations on very high frequency transactions routinely produced by financial markets. Clearly, the notion of market "role" does not have a unique definition. In this paper

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we adopt the general network-analytic notion of market role as induced by relational patterns that differentiate one market actor from another (White, 1981a).

The fluidity of their role structure makes financial markets particularly fragile and susceptible to behavioral contagion (or “herding”) turning market participants into “sellers” or “buyers” suddenly, and all at once. What mechanisms stabilize financial markets under such extreme conditions of role fluidity? More specifically, what resource allocation mechanisms stabilize flows of financial resources among market participants? When and where are these mechanisms more likely to operate?

The partial answer we provide to these orienting questions focuses on generalized exchange (or indirect reciprocity) as a mechanism capable of stabilizing market flows. Generalized exchange removes the need for immediate reciprocation by decoupling market roles and obligations in time, thus alleviating the effects of uncertainty related to variations in patterns of resource availability. Building on the network-theoretic notion of role as a pattern of relations, our analysis of generalized exchange in financial markets focuses on localized relational structures – “on social roles from the perspectives of individual actors,” as it were (Breiger and Pattison, 1986, p.215).

Generalized exchange has long been understood as a fundamental social mechanism stabilizing asymmetric relations through a chain of acts of exchange that cycles back to the initial “givers” – thus eventually making them “receivers” of resources (Mauss, 1954). For generalized exchange to emerge: “The values have to flow through all the parties in a cycle before a giver can become a taker” (Bearman, 1997, p.1389). We adopt this definition of generalized exchange as a micro-relational mechanism that simultaneously shapes – and emerges from the role structure that binds market participants. We depart from extant research on interorganizational exchange and dependence relations by emphasizing the contingent value of network mechanisms – rather than their general rule-like, normative effect on the stability of exchange systems (Ekeh, 1974). We identify time and value as two major contingency factors constraining when and where generalized exchange is likely to emerge and operate as a market reproduction mechanism (White, 2008, p.83).

We theorize that generalized exchange involves a process of learning under uncertainty that operates only slowly over time. Market participants *learn* that being “givers” will eventually make them “receivers” of valuable resources. Similar processes of learning have been richly documented in studies of interorganizational networks (Powell et al., 1996) and economic development (Sabel, 1993). But learning social norms requires time. And norms are not learned instantly and homogeneously everywhere. In consequence, we predict that generalized exchange will facilitate transactions in the longer- but not in the shorter-term. We argue that the effect of generalized exchange will vary considerably across material conditions for exchange. More specifically, we predict that generalized exchange will affect negatively the likelihood of observing exchange events involving larger amounts of resources. This happens because generalized exchange exposes participants to risks of potential opportunism. The level of risk involved in asymmetric exchange increases with the value of transactions.

We test these predictions on data that we have extracted from a major on-line trading platform recording the complete sequence of financial transactions on a major European interbank market for liquidity – a segment of financial markets where banks participate to settle their contingent balance sheet liquidity constraints established by monetary authorities. The data on transactions that we analyze are precise to the second. Our sample contains the complete sequence of second-by-second interbank transactions observed over a period of approximately three years. We focus on the market for overnight liquidity because it provides an almost ideal illustration of an institutional setting where roles emerge from interaction (Leifer, 1988). This is the case because in this institutional segment of the financial market, the roles of seller (“giver”) and buyer (“receiver”) are exchangeable to an extent that would be hard to imagine in other kind of market (White, 1981b).

We find clear evidence that the effects of generalized exchange on financial markets vary significantly across temporal and material conditions of exchange. The study adds considerable detail to our understanding of how and when network effects operate, and our ability to predict how and when specific mechanisms are likely to emerge to shape economic behavior. The results of the study also contribute to a more contextual understanding of the mechanisms that stabilize asymmetric exchange in large-scale, decentralized social systems of which markets are one example.

2. Generalized exchange in financial markets

Because “humans are the champions of reciprocity” (Nowak and Sigmund, 2005, p.1291), asymmetric exchange is hard to explain. It manifests itself as a unilateral resource transfer, where a sender (or “giver”) transfers valuable resources to a receiver (or “taker”) with no obvious possibility to force or enforce reciprocation.[1] The social process that transforms initial givers of material resources into eventual receivers through a directed chain of exchange events is of distinctive sociological interest because it revels the intimate connection between exchange and solidarity (Bearman, 1997).

Generalized exchange affects solidarity because it strengthens the integrative bonds among participants in social exchange situations. Generalized exchange accomplishes this feat by reducing uncertainty about future availability of resources (Uehara, 1990), producing signals of trustworthiness and commitment (Barclay and Willer, 2007), relaxing the need of immediate reciprocation (Bearman, 1997), and by contributing to a sense of diffuse moral obligation (Adler and Kwon, 2002). Revisiting and developing further a classic anthropological insight (Levi-Strauss, 1969), Molm et al. (2007) provide recent experimental evidence that generalized exchange supports forms of solidarity stronger than restricted exchange (or “direct reciprocity”). This happens because generalized exchange “ensures solidarity by binding all members into a chain of univocal prestations, embedding each block in a network of debt and obligation” (Bearman, 1997, p.1406).

“Chains of univocal prestations” embedded in “networks of debt and obligation” are defining features of financial markets – globally decentralized systems structured by networks of technology-mediated transactions (Knorr-Cetina and Bruegger, 2002). While the financial market may not be the most obvious setting to look for evidence of “solidarity” and “moral obligation,” the concept of market *stability* is frequently discussed as a desirable property of markets emerging from the collective trust that participants are able to build in the market that ties their individual interests to a common fate (O’Hara, 2004). Because it encourages perceptions of trust, commitment and social unity (Molm et al., 2007), and because of its association with expectations of private and collective benefits (Simpson et al., 2018), and its tendency to promote higher levels of participation (Yamagishi and Cook, 1993), generalized exchange could play an important role in ensuring the stability of financial markets.

One thing that markets as institutions do is turning exchange relations – transactions, more specifically – into local roles (White and Eccles, 1987; Bearman, 1997), which are then articulated into global role structures through the reproductive forces of repeated exchange (White, 2002; Leifer and White, 2004). The role structure of financial

[1] A number of recent studies focus on the effect of receiving on the individual propensity to give (Mujcic and Leibbrandt, 2018) or “pay it forward” (Tsvetkova and Macy, 2014). Here we focus on a different social process – one that is *triggered by giving*, rather than receiving. Simpson et al. (2018, p.89) call “generalized reciprocity” the former process, and “indirect reciprocity” the latter. What we call “generalized exchange” in this paper is what Simpson et al. (2018) call “indirect reciprocity.”

markets is considerably more fluid than that of consumer or producers' markets (White and Eccles, 1987) – with participants able to switch relatively freely and costlessly between "buyer" and "seller" roles. Because these roles in financial markets are contingent on individual transactions, no other institutional system of exchange better reveals the tendency of interaction – taking the form of flows of transactions in the specific case of financial markets – to induce social roles (Leifer, 1988). This provides an additional reason to expect that the stabilizing force of generalized exchange might be at work in financial markets to ensure stability in the face of uncertainty. Obviously, generalized exchange should be considered a hypothesis rather than an assumption about how any market might work.

Generalized exchange is problematic for at least two reasons that, we argue, contribute to define the conditions for its emergence and sustainability in markets. The first is that the collective construction of generalized exchange in markets is not instantaneous and is likely to require at least some time to emerge. This is the case because market participants need time to learn how much they can rely on generalized exchange as a resource redistribution mechanism. This trial-and-error learning simply cannot operate instantaneously as it emerges from time-ordered sequences of learning opportunities (Denrell and March, 2001).

Generalized exchange works by decoupling "time to give" form "time to receive," thus posing the problem of the time horizon necessary for its emergence. With the exception of a limited number of recent attempts to distinguish between short- and long-term effects of network mechanisms (Kitts et al., 2017; Amati et al., 2019; Bianchi, 2019; Bianchi and Lomi, 2022), extant research has typically maintained the implicit assumption that network mechanisms operate instantaneously – rather than being contingent on "the network of other cases and prior times" (Abbott, 1995, p.94). In the case of the European market for liquidity that we examine in the empirical part of the paper, for example, a market participant is likely to take some time to discover the extent to which "giving" liquidity to another bank eventually facilitates "receiving" liquidity at a later time and from a different credit institution. While we do not know how long this learning process might take, we know that it will not be instantaneous. For this reason, we expect that generalized exchange will be unlikely to support market transactions in the short-term, but we rather expect that it will emerge in the longer-term as an element of market stabilization.

The second element contributing to make generalized exchange problematic in markets and other exchange systems with no centralized control concerns the unavoidable tension between individual and collective interests that generalized exchange entails (Yamagishi and Cook, 1993). Because "individuals may be motivated to take from the system without giving back to it" (Simpson et al., 2018, p.88), generalized exchange provides little insurance against free riding behavior of market participants who might be tempted to interrupt the giving/receiving cycle simply by not "paying it forward" (Baker and Bulkley, 2014). For this reason, it is likely that generalized exchange will be associated with the tendency of market participants to become more risk averse and make fewer resources available as the value of transactions in which they are involved increases – a behavioral phenomenon generally known as "stake effect" (Bouchouicha and Vieider, 2017). The potential for free riding (Takahashi, 2000) makes generalized exchange unlikely to operate in settings where the value of the resources being exchanged is considerable. We would expect this to be particularly the case in situations where exchange events are decoupled in time – as discussed in point one above. In such cases, different types of closure mechanisms are likely to provide more robust insurance against free riding and opportunism (Coleman, 1988).

3. Empirical setting and data

The empirical setting of this study is the European interbank market, a financial market that channels liquidity from institutions with excess to those with deficit of liquid assets. The European interbank market allows European credit institutions to extend loans to one another with two main purposes (Gabrieli, 2011). First, satisfying banks' liquidity financing needs with the aim of managing anticipated and non-anticipated short-term liquidity imbalances. Second, fulfilling the reserve requirements imposed by the European Central Bank with the aim of promoting suitable liquidity management programs. European interbank market transactions have an immediate effect on the global economy (Gabbi et al., 2013). In fact, variations in interbank rates are rapidly transmitted to the whole term structure, thus affecting borrowing conditions for both firms and households. Interbank rates underlie derivative contracts like interest rate swaps or short-term interest rate futures, commonly used by financial institutions to hedge against variations in short-term interest rates. This is why a well-functioning interbank market is the premise for central banks to trade liquidity efficiently, achieve the desired level of interest rates, and transmit the monetary policy.

During the period of observation, the interbank market played a crucial role in the reallocation of liquidity originally supplied by the national central banks (Wiemers and Neyer, 2003). A fundamental reason for this reallocation is the need to provide market heterogeneous participants with an easy access to liquidity. Indeed, when borrowing from the central bank, credit institutions face different costs based on their different capacity to provide adequate collateral. In contrast, when borrowing on the interbank market, and especially on special segments for unsecured loans, banks do not face the cost of holding eligible assets.

In the interbank *money* market, for example, financial instruments are traded as cash equivalent and most interbank loans are for maturities of one week or less, with the majority being *overnight*. When involved in overnight loans, borrowers pay back the borrowed funds – plus the charged interest rate – at the beginning of the next trading day.

One prominent example of unsecured interbank money market is e-MID, the only *electronic market for interbank deposits* in the Euro area. Because of its special real-time gross settlement system, e-MID guarantees that liquidity will 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 European Central Bank, consisting of a time frame of approximately sixweeks (30 trading days) in which credit institutions must maintain a specified level of funds calculated on the basis of banks' balance sheets.

The e-MID market takes the form of a multilateral screen-based trading platform where registered banks can electronically transfer interbank deposits by adhering to the market regulation. Credit contracts have a wide range of maturities, ranging from overnight (approximately 85%) to one year. For certain maturities that include overnight contracts, the platform distinguishes between *regular* transactions – with a minimum amount of EUR 0.05 million – and *large* transactions – with a minimum amount of EUR 100 millions. We use this institutional definition to distinguish "regular" (ON) from "large" (ONL) transactions.

Participants to the e-MID platform enjoy the benefits of transparency and minimal search costs. Trades are public in terms of duration, amount, rate and time. Credit institutions that enter the electronic market can see all the negotiations taking place on the platform – i.e., what banks are asking or offering liquidity. *Quoters* and *aggressors* are the two roles communicating through the market interface. The e-MID trading platform is a quote-driven market. Therefore, market participants willing to trade can make their interest public to their possible counterparts by acting as *quoters* and proposing the setting of the loan contract as Fig. 1 documents. If the deal attracts a counterpart, this acts as an *aggressor* by sending the order back to close the deal. Aggressors are characterized by their affiliation to either side of the market interface. Aggressors that respond to quoters asking for capital are associated with a "sell" identity label. Accordingly, aggressors that are in need of borrowing money from quoters are associated with a "buy" identity label. This type of negotiation is carefully depicted in Fig. 1. Eventually,

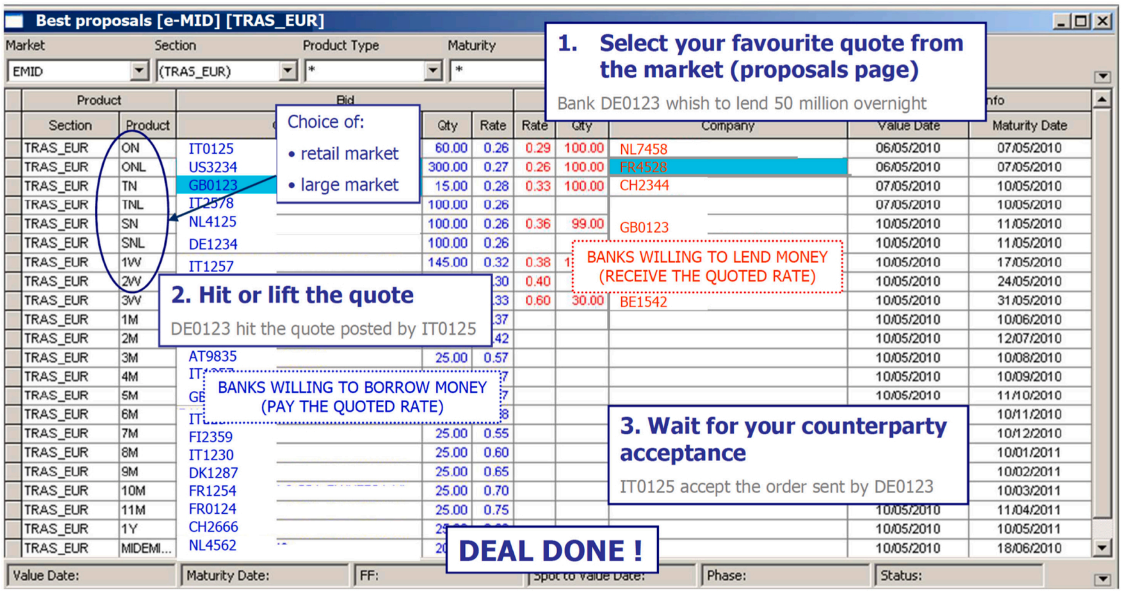


Fig. 1. Trading mechanism on the e-MID platform. The e-MID proposal page distinguishes between credit institutions that are willing to borrow and lend money. The example shows the initiative of bank DE0123 (a German bank) wishing to lend 50 million overnight. DE0123 has two options. First, DE0123 could act as a quoter and post a selling order on the platform. Alternatively, DE0123 could search for a convenient buying order and hit it. This is the scenario described in the picture, where DE0123 hits the quote posted by IT0125 (an Italian bank) and ultimately sells its excess of liquidity.

in terms of market roles, aggressors may act both as liquidity “givers” or “receivers.” They act as liquidity borrowers (“receivers”) when they are associated with a “buy” label, and as liquidity lenders (“givers”) when they are associated with a “sell” label.

Transactions on the e-MID market are collected in time-stamped data sets in which each line reports the distinctive features of the corresponding credit contract. Transactions occur with very high-frequency and their time stamps are precise to the second. We collected second-by-second data from the e-MID trading platform from January 2005 to August 8, 2007 – a period of market stability that anticipates a series of market turmoils that have regularly agitated markets in the last fifteen years.[2] On average, a new money transfer event occurs every 1.5 and 11 min in the ON and ONL segments, respectively.

The resulting data set is composed of a time-ordered sequence of 271,896 overnight credit contracts, with 239,028 credit contracts institutionally classified as regular (ON) transactions and the remaining 32,868 classified as overnight large (ONL). In both settings, the majority of European banks that trade on the e-MID platform ask for overnight liquidity. In the regular ON segment, aggressors have hit 73.76% bid quotes. In the ONL one, the same percentage increases to 80.34%.

Overall, the sample includes 194 credit institutions from 16 European countries. The ON and ONL segments have 190 and 110 banks, respectively. Most of the credit institutions are active in both segments, with 84 credit institutions being involved exclusively in ON contracts. Only 4 banks trade exclusively large amounts of overnight liquidity.

The majority of European banks act as both buyers and sellers of liquidity, thus showing a general propensity toward role-switching behaviors that, in turn, mark reciprocity as the fundamental mechanism of financial markets. During the period of observation, only 6 banks are “pure receivers" of funds (out-isolates), and only 15 are “pure providers” (in-isolates) in the regular ON segment of the market.

4. Model and measures

Building on the foundational work of Butts (2008), the model that we introduce in this study provides a suitable analytical framework for the analysis of time-ordered sequences of relational events – i.e., interactions between market participants observed at specific points in time. In our empirical application, participants are European banks and financial institutions, while relational events are high-frequency transfers of overnight funds observed during a typical trading day.

Relational event models (REMs) afford a high fidelity representation of our time-stamped, high-frequency data (Stadtfeld and Block, 2017). REMs maintain in the analysis the same level of precision of the observed data. The REM that we adopt in the empirical part of the study is part of the more general class of point-process models for social interaction (Perry and Wolfe, 2013), and is aligned with other specifications recently used in a number of empirical studies (Lomi et al., 2014; Vu et al., 2015,2017; Amati et al., 2019).

A detailed description of the current REM specification is illustrated in Bianchi and Lomi (2022), which builds on the original work of Vu (2012, p.110), and more recent developments – e.g., (Vu et al., 2015, 2017) by: (i) incorporating intensity-based statistics to model the strength of relations between senders and receivers; (ii) allowing the predictive value of past events to decay over time; (iii) computing network effects over time horizons of different length, and (iv) adopting a stratification procedure that alleviates concerns about how heterogeneity of the sender units may affect the empirical estimates.

The core features of point-process models (Cox and Isham, 1980) for directed social interaction (Perry and Wolfe, 2013) may be of particular value in applications based on data sets larger than those typically used in network studies based on more conventional analytic techniques.

4.1. Model definition

At its core, the REM involves a count process N defined on network edges between a sender i and a receiver j. Let,

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

[2] On August 9, 2007, the decision of a major French credit institution to freeze three large investment funds because of problems in subprime securities affected traders’ trust in the regular functioning of financial markets, and initiated a collection of market jolts that eventually revealed the subprime mortgage crisis the year after. In a recent empirical work Zappa and Vu (2021) analyzed the effects of the global financial crisis on the micro-mechanisms of market connectivity.

In line with similar REM specifications (Vu et al., 2011; Perry and Wolfe, 2013; Vu et al., 2015,2017), the counting process $N_{ij}(t)$ is modeled through its *conditional intensity (or rate) function* λ (t, i, j).

$$\lambda(t,i,j|\boldsymbol{H}_{t^-}) = R_{ij}(t)\cdot\lambda_0(t)\cdot\exp[\boldsymbol{\theta}^{\intercal}\boldsymbol{s}(t,i,j)], \tag{1}$$

where $\boldsymbol{H}_{t^-}$ is the history of all past relational events right before time t, $\boldsymbol{s}(t,i,j)$ is a vector of time-dependent network statistics, and $\boldsymbol{\theta}$ is the vector of corresponding parameters to estimate. $R_{ij}(t)$ is the "at-risk" indicator that takes value 1 if sender i can extend resources to receiver j at time t, and 0 otherwise. Defining the risk set for the network units of interest means specifying one or more non overlapping time intervals where relational events may occur.

Our model specification draws on Perry and Wolfe (2013) who include a sender-stratified conditional intensity function that absorbs the heterogeneity associated with unobservable characteristics of liquidity providers – i.e.,

$$\lambda(t,i,j|\boldsymbol{H}_{t^-}) = R_j(i,t)\cdot\lambda_{i0}(t)\cdot\exp\left[\boldsymbol{\theta}_r^{\intercal}\boldsymbol{s}(t,j) + \boldsymbol{\theta}_e^{\intercal}\boldsymbol{s}(t,i,j)\right]. \tag{2}$$

This sender-stratified approach recently adopted also by Zappa and Vu (2021) reduces computational complexity, but does not alllow sender effects $\boldsymbol{\theta}_s^{\intercal}$ to be estimated. Receiver $\boldsymbol{\theta}_r^{\intercal}$ and edge (dyadic and extra-dyadic) $\boldsymbol{\theta}_e^{\intercal}$ statistics are estimated instead. Receiver and edge statistics may be globally identified as $\bm \theta^{\intercal}$.

4.2. Model estimation and interpretation

We treat the conditional intensity function $\lambda_{i0}(t)$ as a nuisance parameter and estimate the vector of network parameters $\boldsymbol{\theta}$ in (1) via partial likelihood (Cox, 1975).

The inferential strategy is based on the following general form of the partial likelihood:

$$PL(\boldsymbol{\theta}) = \prod_{e\in E}\frac{\exp[\boldsymbol{\theta}^{\intercal}\boldsymbol{s}(t_e,i_e,j_e)]}{\sum_{(i,j)}R_{ij}(t_e)\exp[\boldsymbol{\theta}^{\intercal}\boldsymbol{s}(t_e,i,j)]}, \tag{3}$$

where E is the set of all relational events during the observation time and R_{ij}(t_{e}) is the risk set for the event e at time t_e.

In empirical applications, large networks of events produce correspondingly large risk sets. Even if sparsity can be exploited to make computation more efficient (Vu et al., 2011; Perry and Wolfe, 2013), the presence of temporal network statistics requires particular care. To make partial likelihood inference feasible, we combine stratification (Vu et al., 2015) and nested case-control sampling (Borgan et al., 1995).

Adopting stratification as illustrated in (1) alters the partial likelihood in (3) – i.e.,

$$PL(\boldsymbol{\theta}) = \prod_{e\in E}\frac{\exp[\boldsymbol{\theta}^{\intercal}\boldsymbol{s}(t_e,i_e,j_e)]}{\sum_{j}R_j(i_e,t_e)\exp[\boldsymbol{\theta}^{\intercal}\boldsymbol{s}(t_e,i_e,j)]}, \tag{3a}$$

where the risk set $R_j(i_e, t_e)$ includes only the edges between sender i_e and the set of its receivers at time t_e.

Under the nested case-control sampling approach, $R_j(i_e, t_e)$ is a case-control dataset of network statistics nested in event times – i.e., a dataset in which the cases are the statistics (t_e, i_e, j_e), while the controls are (t_e, i_e, j), with $j \neq j_e$. Consistency and asymptotic results of nested case-control sampling are discussed in Borgan et al. (1995).

Thanks to the sparsity of network statistic changes, an adequate number of controls is sampled as suggested by Lerner and Lomi (2020). In the current stratified-by-sender approach, $\lambda_{i0}(t)$ helps to reduce the computational complexity and to increase the efficiency of the sampling scheme.

The outcome variable associated with the observed relational event takes value 1 for events (or "cases") and 0 for nonevents (or "controls"), while the explanatory variables are the network statistics (t_e, i_e, j_e) and (t_e, i_e, j). The partial likelihood is maximized by the same estimation algorithm used to estimate conditional logistic regression models (Vu et al., 2015). Standard errors of parameter estimates are obtained by computing the inverse of the Hessian matrix.

We implemented an ad-hoc Java application to generate nested case-control data from event streams, which are then fed into a Cox proportional hazard procedure. An example of such procedure is the R-based *clogit* function that computes a conditional logistic regression for matched case-control studies.[3]

Even if our REM is ultimately defined in terms of a conditional logistic regression, interpreting parameter estimates requires particular care. Quantities of interest like odds ratios can only be interpreted heuristically as the fundamental interdependence among network statistics makes *ceteris paribus* assumptions particularly implausible. In discussing the results, we provide an interpretation of parameter estimates that is based on the sign and the odds ratios of the parameters.

A significant and positive value for direct reciprocity (or "restricted" exchange), for example, would be taken as evidence of role switching – i.e., the tendency of market participants to act both as givers and receivers of funds with their *vis-a-vis* exchange partners. Similarly, a significant and positive value for transitivity would be taken as evidence that transactions are more likely to be observed between organizations sharing the same partners.

4.3. Network statistics

Following a well-established practice in statistical modeling of event networks (Butts, 2008; Brandes et al., 2009), statistics are defined as counts of time-ordered relational events based on temporal patterns of dependence commonly associated with micro-mechanisms of theoretical or empirical interest.

In REMs network statistics may account for temporal dependencies among past events (Butts, 2008). Following Vu et al. (2015), we assume that the temporal relevance of a relational event decreases according to a power law distribution $f(t, T_{ij}^e, \alpha)$ such that

$$f\left(t, T_{ij}^e, \alpha\right) = \frac{1}{\left(t - T_{ij}^e\right)^{\alpha}}, \tag{4}$$

where t is the current time, T_{ij}^e is the exact time of the relational event e on the edge (i, j), and α is the time-decay parameter. When $\alpha = 0$, all the past events contribute equally to the computation of network statistics. When $\alpha > 0$, recent events have a greater impact. The larger the value of α, the lower is the impact of past events on the computation of network statistics. This feature is desirable in empirical settings where relational events occur with high frequency, and the organizational activity is concentrated within temporal frames of short and fixed length. We set the decay parameter so that it consistently weights past events in accordance with the European Central Bank calendar for three-month longer-term refinancing operations ($\alpha = 0.5$).

Our empirical specification incorporates two distinct classes of network statistics. First, degree-based statistics that count the number of directed relational events embedded in local structures of network dependence. Second, their intensity-based counterparts that are weighted by the number of *unique* recipients. To account for temporal variations in the sequences of relational events, degree-based statistics unfold within short- and long-term temporal frameworks, while their intensity-based counterparts are time-weighted. This distinction allows us to remove the collinearity that may be present between degree- and intensity-based statistics.

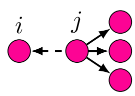
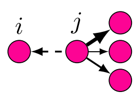
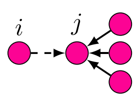
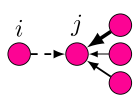
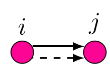
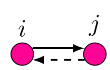
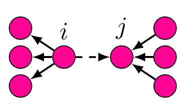
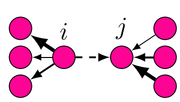
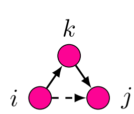
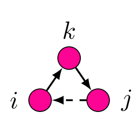
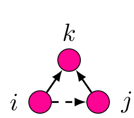
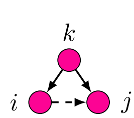
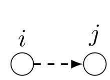
The network statistics based on relational events ultimately

[3] Equivalent routines for the estimation of network effects are available in commercial software like, for example, the *PHREG* function in SAS.

crystallize into specific micro-mechanisms of structural dependence that are summarized in Table 1.

We model preferential attachment (Newman, 2001) by means of degree- and intensity-based statistics. To model activity, we use "out-degree" and "out-intensity" statistics – both defined as functions of the number of borrowers for each lender. To model popularity, we use "in-degree" and "in-intensity" statistics instead – both defined as functions of lenders for each borrower. While the out-degree statistic is a simple count of the number of borrowers per each lender, its intensity-based counterpart is a weighted sum of borrowers per each lender, in which the weights account for both the number of unique borrowers per lender, and the temporal relevance of the relational flow of resources form a sender to a receiver. In-degree and in-intensity statistics are defined in a similar fashion.

Table 1
Network statistics defined in the REM.

Network Statistic	Representation	Formula
Out-degree		$\sum_{i \neq j} \mathbb{1}\left[N_{ji}(t^-) > 0\right]$
Out-intensity		$\frac{1}{\textit{out-degree}\,(t,j)} \sum_{i \neq j} \sum_{e=1}^{N_{ji}(t^-)} \frac{1}{\left(t - T_{ji}^{e}\right)^{\alpha}}$
In-degree		$\sum_{i \neq j} \mathbb{1}\left[N_{ij}(t^-) > 0\right]$
In-intensity		$\frac{1}{\textit{in-degree}\,(t,j)} \sum_{i \neq j} \sum_{e=1}^{N_{ij}(t^-)} \frac{1}{\left(t - T_{ij}^{e}\right)^{\alpha}}$
Familiarity		$\sum_{e=1}^{N_{ij}(t^-)} \frac{1}{\left(t - T_{ij}^{e}\right)^{\alpha}}$
Reciprocation		$\sum_{e=1}^{N_{ji}(t^-)} \frac{1}{\left(t - T_{ji}^{e}\right)^{\alpha}}$
Assortativity by degree		$\textit{out-degree}(t,i) \times \textit{in-degree}(t,j)$
Assortativity by intensity		$\textit{out-intensity}(t,i) \times \textit{in-intensity}(t,j)$
Transitive closure		$\sum_{k \neq i,j} \left[\mathbb{1}_{N_{ik}}(t) \wedge \bar{\mathbb{1}}_{N_{ki}}(t)\right] \wedge \left[\bar{\mathbb{1}}_{N_{jk}}(t) \wedge \mathbb{1}_{N_{kj}}(t)\right]$
Generalized exchange		$\sum_{k \neq i,j} \left[\mathbb{1}_{N_{ik}}(t) \wedge \bar{\mathbb{1}}_{N_{ki}}(t)\right] \wedge \left[\mathbb{1}_{N_{kj}}(t) \wedge \bar{\mathbb{1}}_{N_{jk}}(t)\right]$
Shared borrowers		$\sum_{k \neq i,j} \left[\mathbb{1}_{N_{ik}}(t) \wedge \bar{\mathbb{1}}_{N_{ki}}(t)\right] \wedge \left[\mathbb{1}_{N_{jk}}(t) \wedge \bar{\mathbb{1}}_{N_{kj}}(t)\right]$
Shared lenders		$\sum_{k \neq i,j} \left[\bar{\mathbb{1}}_{N_{ik}}(t) \wedge \mathbb{1}_{N_{ki}}(t)\right] \wedge \left[\bar{\mathbb{1}}_{N_{jk}}(t) \wedge \mathbb{1}_{N_{kj}}(t)\right]$
Node matching		$\mathbb{1}\left[c(t,i) = c(t,j)\right]$

Notes. Network statistics introduced in our model specification. The term $N_{ij}(t)$ refers to the number of relational events flowing from social unit i to unit j at time t. The term $f(t, T_{ij}^{e}, \alpha)$ is the decay function accounting for the temporal relevance of previous relational events. The term $1_{N_{ik}}(t)$ is a compact notation for $1[N_{ik}(t^-) > 0]$, with *1* being an indicator function that takes value 1 if the condition in the brackets is satisfied, and 0 otherwise. Finally, the term c indicates a nodal covariate.

In our context *reciprocity* refers to the tendency of banks that have been providers of liquidity in the past, to become receivers of liquidity in the future. This is important in our context because reciprocity is directly related to role switching because "Dyadic exchanges governed by a norm of reciprocity lock actors into "endless" exchanges, as each alternates occupying giver and taker roles" (Bearman, 1997, p.1390). We expect a positive and significant effect of reciprocity consistent with our understanding of the role structure of financial markets.

Familiarity refers to the tendency of banks that have traded liquidity in the past to repeat the same transaction in the future. The associated statistic indicates that in a collection of consecutive relational events, senders and receivers stick to their original roles (Vu et al., 2017). Familiarity also signals the presence of relational inertia that tends to stabilize flows of transactions. For this reason, the tendency toward repeated transactions with the same partners that familiarity reveals is one of the basic processes through which resource flows reproduce.

Assortativity refers to the tendency of network nodes to "mix" on the basis of similarity in their patterns of relational activities (Newman, 2002). Assortativity may be expressed in terms of degree (Snijders et al., 2010) or intensity (Vu et al., 2017). Assortativity statistics are defined as an interaction between lenders' out-degree (or out-intensity) and borrowers' in-degree (or in-intensity). Significantly positive estimates of degree-based assortativity parameters, reveal a tendency of banks lending to many borrowers preferentially to lend to banks borrowing from many lenders. Significantly positive estimates of intensity-based assortativity parameters, reveal a tendency of "heavy" lenders preferentially to transfer liquidity resources to "heavy" borrowers – and hence strengthen the boundaries around market roles. For this reason, we tend to interpret positive estimates of assortativity parameters as an indirect signal of market role specialization.

Generalized exchange involves an indirect form of reciprocity requiring at least three parties where "no party gives to the party from whom he receives" Ekeh (1974, p.50). The associated statistic is a three-cycle (triad 030 C) represented as $i \to k \to j \Rightarrow j \to i$ (Breiger and Ennis, 1997, p.76). Positive estimates of parameters associated with generalized exchange indicate the tendency of resources to flow back to the initial initiator of the cycle. We choose this specification for generalized exchange because a three-cycle is the smallest possible subgraph that may be defined to represent indirect reciprocity.[4]

Transitive closure measures the extent to which future relational events are made more likely by the occurrence of past events from the sender to the receiver through a common third party – i.e., $i \to k \to j \Rightarrow i \to j$. Transitive closure and cyclic closure share the same antecedent structure – i.e., the two-path sequence. A positive estimate of parameters associated with transitive closure detects a tendency toward a specific form of path-shortening whereby a direct connection becomes more likely to be observed between participants connected indirectly through a two-path.

Shared partners statistics are associated with the general notion of balance (Snijders et al., 2010, p.58). Shared partners statistics measure the extent to which future relational events are more or less likely to be observed between nodes with common resource dependencies. More specifically, we distinguish between two types of shared partners configurations. We define the *shared borrowers* statistic as the tendency of financial resources to flow between lenders sharing a mutual borrower. In the same vein, the *shared lenders* statistic refers to borrowers sharing a mutual lender. Shared partners statistics represent local forms of structural equivalence. Positive estimates of parameters associated with shared partners statistics may be interpreted as the tendency of participants occupying similar network positions to collaborate.

Fig. 2 illustrates how some micro-mechanisms that are of our specific interest emerge from time-ordered sequences of relational events. On a solid line that represents time, we depict individual acts of exchange that bring together actors A, B and C in a way that specific dyadic or extra-dyadic micro-mechanisms arise. Examples of network-like structures of dependence are familiarity, reciprocity in its restricted and generalized forms, and transitivity. More specifically, Fig. 2a shows that local structure of dependence may emerge across distinct temporal frames. In our illustrative example, colored structures arise within short-time frames, while white structures arise within longer temporal frames.

Fig. 2b focuses on direct reciprocity and generalized exchange and shows how these structures of dependence arise as functions of their antecedent mechanisms. Regarding direct reciprocity, for example, the relational event connecting A to B at time $t3$ works as an antecedent for the relational event flowing in the opposite direction at a later time $t4$. Similarly, the two-path $C \to B \to A$ opened at time $t7$ and realized at time $t8$ eventually crystallizes into a cyclic triad via $A \to C$ at time $t10$.

5. Results

We report the estimates of models that include both degree- and intensity-based statistics. Degree-based statistics account for a time window that defines short- and long-term-based network statistics. Intensity-based statistics account for a time-weighting scheme that measures the strength of relations between senders and receivers. We define degree-based, short-term statistics over a time horizon of 30 days corresponding to credit institutions' calendar of reporting on maintenance of reserve margins.

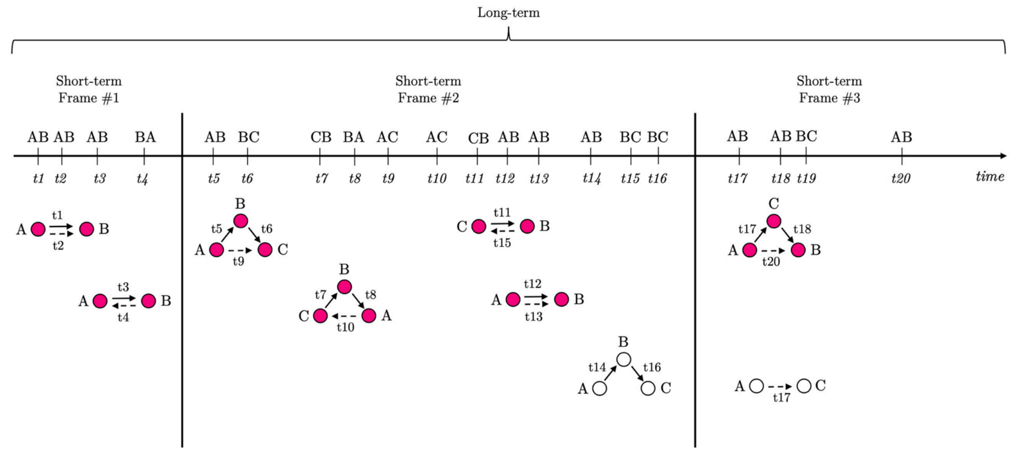
5.1. Regular overnight transactions

ON transactions represent the great majority of interbank credit extensions in the e-MID market (Hatzopoulos et al., 2015). Empirical results reported in Table 2 are generally in line with those obtained in extant empirical studies of trading networks in this market (Finger and Lux, 2017; Bianchi et al., 2020). The model seems to capture with accuracy the effects of activity, popularity, reciprocity, and closure.

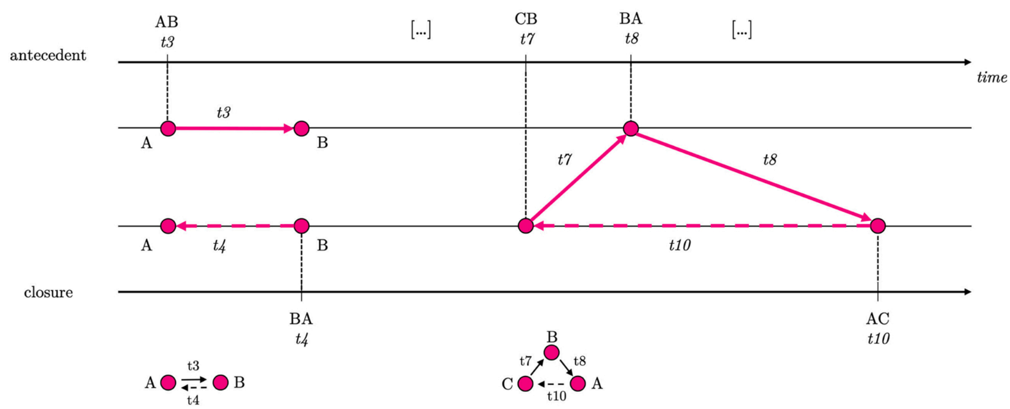
The REM presented in this paper is conceptualized as a conditional logistic regression for matched case-control data. Accordingly, the interpretation of network-based effects on the basis of odds ratios should be considered as heuristic (Bianchi and Lomi, 2022). To facilitate the presentation of empirical results, we focus primarily on the dynamics of "restricted" and "generalized exchange." The illustration of direct reciprocation logically precedes the discussion of generalized exchange. Other dyadic and extra-dyadic network effects included in the model are interpreted as control factors. All the statistics in the model specification are standardized to ensure numerical consistency and comparability of the estimates. In consequence, qualitative interpretation of the estimates is presented in terms of change in the dependent variable – i.e., the probability of observing the next event – associated with change in one standard deviation of the corresponding "independent" co-factor.

The positive and significant effect of direct reciprocation ("restricted exchange") implies a significant tendency of lenders ("givers") and borrowers ("receivers") to exchange their market roles. The odds implied by degree-based short-term directed reciprocation (*exp* $(0.181) = 1.20$) suggest that the more banks have been involved in reciprocal exchange in the past 30 days, the more they will tend to reciprocate transactions in the next calendar month. More precisely, *within any lender-borrower dyad*, in a period of 30 days, an increase of one standard deviation in the number of reciprocated transactions increases, on average, the odds that the next transaction will be reciprocated – i.e., imply a role-switch – by approximately 20%. The same reasoning could be extended to degree-based long-term reciprocation. The corresponding odds (*exp* $(0.075) = 1.08$) suggest that banks involved in reciprocal giving behaviors in periods longer than 30 days still tend to reciprocate

[4] Longer cycles of length four, five etc. would be obviously possible – but also more difficult to link to results reported in prior network research based on established modeling best practice (Pattison and Robins, 2002). In the absence of prior research, estimates of parameters associated with longer cycles of events would be hard to interpret.



(a) Structured event sequences. Magenta-colored structures emerge in short-time frames. White-colored structures emerge in the long-term.



(b) Formation of directed and generalized reciprocity from sequences of relational events. For each social mechanism is reported its antecedent.

Fig. 2. Emergence of direct and indirect reciprocity from sequences of time-ordered events.

transactions in the future, even if to a lesser extent. For ON transactions, the propensity to directed reciprocal exchange does not emerge when considering intensity-based direct reciprocation – i.e., reciprocation between *well-established trading partners*. This means that well-established lender-borrower dyads tend to stick to their roles of liquidity givers and takers regardless of they reporting activities and refinancing operations. Interaction between established partners represents a recognized element of stability in overnight interbank lending markets (Afonso et al., 2013).

The odds implied by short-term generalized exchange ($exp(-0.181) = 0.83$) suggest that, within one calendar month, an increase of one standard deviation in the number of open three-cycles – i.e., two-paths – decreases, on average, the odds that the next transaction will close a two-path by $(0.83 - 1)*100 = 17\%$. Generalized exchange emerges in the longer-term instead. In fact, the odds implied by long-term generalized exchange ($exp(0.091) = 1.1$) indicate that, an increase of one standard deviation in the number of open two-paths increment, on average, the odds that the next transaction will be part of a three-cycle by 10%. When generalized exchange occurs, each member of the cycle becomes both a "giver" (or sender) and a "taker" (or receiver) of financial resources – although *not* at the same time. In the longer term, generalized exchange contributes to confound the market role of participants. Even assuming that recent events have a grater impact in determining financial flows that are embedded in local transaction cycles, the tendency toward generalized exchange does not emerge in the short-run. This result provides additional empirical support to our conjecture about the time delay necessary for social mechanisms to reproduce detectable effects.

In the short-term, the tendency of European banks to act as liquidity providers is negative, thus suggesting that market participants typically do not distribute the liquidity that they have collected in the past 30 days. The same conclusion holds when considering preferential trading relationships and longer temporal frames. The negative sign associated with the out-intensity parameter, along with a positive sign of long-term out-degree, suggests that periods longer than 90 days are required to let banks emerge as central liquidity providers. In-degree effects are all positive and particularly strong in their degree-based specification. Concerning in-intensity effects and preferential trading relationships, results show that some European banks accept credit extensions from trading partners they have traded in the recent past. Jointly interpreted, these results indicate that in the long-term there is a generalized positive effect of past transfers of ON funds on the current trading activity. Such an effect is particularly strong for those credit institutions that borrow liquidity.

The market for regular ON transactions is disassortative – i.e., banks lending to many do not lend to banks borrowing from many. This short-term tendency toward disassortative mixing increases more than four times in the longer term. A contextual interpretation of disassortative (by intensity) mixing suggests the ability of the market to support exchange between "heavy lenders" and "light borrowers." The effects of

Table 2
Estimated coefficients and corresponding standard errors (SE) of a REM with recency window equal to 30 days and $\alpha = 0.5$.

		ON		ONL	
		Estimate	SE	Estimate	SE
Out-degree	(ST)	-0.124***	(0.008)	-0.087***	(0.018)
Out-degree	(LT)	0.048***	(0.015)	0.213***	(0.034)
Out-intensity	(I, TW)	-0.377***	(0.01)	0.015	(0.016)
In-degree	(ST)	1.176***	(0.02)	1.109***	(0.035)
In-degree	(LT)	0.672***	(0.024)	0.723***	(0.048)
In-intensity	(I, TW)	0.297***	(0.012)	0.209***	(0.024)
Familiarity	(ST)	1.708***	(0.022)	1.258***	(0.03)
Familiarity	(LT)	-0.123***	(0.015)	0.071***	(0.026)
Familiarity	(I, TW)	0.478***	(0.006)	0.525***	(0.019)
Reciprocation	(ST)	0.181***	(0.008)	0.114***	(0.015)
Reciprocation	(LT)	0.075***	(0.009)	0.076***	(0.015)
Reciprocation	(I, TW)	-0.008	(0.006)	-0.061***	(0.015)
Assortativity by degree	(ST)	-0.382***	(0.019)	-0.226***	(0.036)
Assortativity by degree	(LT)	-1.763***	(0.032)	-0.583***	(0.068)
Assortativity by intensity	(I, TW)	-0.400***	(0.013)	-0.035	(0.033)
Transitive closure	(ST)	0.727***	(0.019)	-0.080**	(0.034)
Transitive closure	(LT)	0.609***	(0.022)	0.106**	(0.044)
Generalized exchange	(ST)	-0.181***	(0.011)	-0.002	(0.025)
Generalized exchange	(LT)	0.091***	(0.015)	-0.090***	(0.033)
Generalized exchange	(I, TW)	-0.119***	(0.009)	-0.009	(0.029)
Shared borrowers	(ST)	0.476***	(0.012)	0.184***	(0.028)
Shared borrowers	(LT)	0.124***	(0.017)	-0.047	(0.035)
Shared lenders	(ST)	0.080***	(0.014)	0.078**	(0.031)
Shared lenders	(LT)	0.029	(0.018)	-0.029	(0.035)
Country-match		0.617***	(0.01)	0.180***	(0.013)
Number of observations		717,084		98,604	
AIC		152,276.842		25198.423	

Legend: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Notes. Degree-based short- and long-term statistics are indicated with (ST) and (LT) labels, respectively. Intensity-based time-weighted statistics are indicated with the (I, TW) label.

degree-based disassortativity imply that banks lending to many also lend to banks borrowing from few others.

Introducing familiarity as a control effect affords a richer interpretation of direct reciprocation. With the exception of degree-based long-term familiarity, there is a positive tendency towards the repetition of past transactions. This effect is stronger in the shorter-term. Familiarity turns negative in the longer term, then suggesting that the force of reproduction induced by repeated transactions may be weakened by diversification strategies enacted to seek new partners, and new routes to channel financial flows.

The positive effect of transitive closure across short- and long-term temporal frames reveals the tendency of ON transactions to be organized around clusters of banks that preferably exchange liquidity with the partners of their partners. A positive effect of shared borrowers suggests that ON transactions are facilitated between credit institutions depending from the same sources of liquidity. A positive value of short-term shared lenders suggests that exchange of liquidity is more likely to be observed between banks sharing the same borrowers. We notice that these different forms of closure coexist with generalized exchange, but do not substitute for it.

5.2. Overnight large transactions

Unlike recent empirical studies of the European interbank market focusing exclusively on overnight (ON) transactions (Zappa and Vu, 2021), we exploit data on overnight large (ONL) transactions to examine differences in network mechanisms determined by quasi-experimental variation in material conditions of exchange. We now fit to ONL transactions – i.e., overnight transactions whose amount is larger than 100 million EUR – the same model that we previously fitted to ON transactions. Estimates of direct reciprocation reveal both similarities and differences across the two market segments. The tendency toward degree-based reciprocation remains positive within short and long temporal frames. However, the propensity toward intensity-based reciprocal exchange is significantly negative, then suggesting that, for larger transactions, buyer and seller roles are more specialized and less fluid. The odds implied by short-term degree-based reciprocation ($exp(0.114) = 1.12$) suggest that sequences of ONL transactions based on restricted reciprocity are less frequent during short-time periods. More specifically, *within any dyad*, an increase of one standard deviation in the number of reciprocated transactions increases, on average, the odds that the next transaction will be reciprocated by 12% – rather than 20% as in the ON segment. The odds implied by long-term degree-based reciprocation ($exp(0.075) = 1.08$) are aligned to those estimated in the ON case. Indeed, in both segments, an increase of one standard deviation in the number of reciprocated transactions increases, on average, the odds that the next transaction will be reciprocated by 8%. In conclusion, regardless of the exchanged amounts, the more banks have engaged in reciprocal exchange in the past, the more they tend to reciprocate future transactions.

Trading dynamics in the ONL segment differ markedly from those in the regular ON segment. With the partial exception of long-term degree-based generalized exchange – that is statistically significant but negative – there is no empirical evidence in support of generalized exchange. Role-switching behaviors implied by exchange cycles are strongly avoided. The odds implied by long-term degree-based generalized exchange ($exp(-0.090) = 0.91$) suggest that an increase of one standard deviation in the number of open two-paths decreases, on average, the odds that the next transaction will be part of a three-cycle by 9%. In line with our conjecture, these results suggest that the effects of generalized exchange vary significantly across material exchange contexts.

Empirical evidence in support of preferential attachment varies when considering ONL transactions. The magnitude of the long-term out-degree effect increases dramatically, thus revealing a tendency of lending activities to become more concentrated. As the non significant out-intensity parameter seems to suggest, large amounts of overnight liquidity are not extended to well-established trading counterparts. The short-term out-degree effect is much lower in magnitude than its ON counterpart, thus suggesting that credit institutions in the ONL segment very rarely introduce large amounts of liquidity within 30 days. In contrast, in-degree parameters are similar in both institutional settings, therefore indicating that borrowers of overnight liquidity do not change their trading strategies on the basis of monetary values.

Like its ON counterpart, the ONL network is disassortative. In the ONL segment, triadic effects of shared partners work in the short-term only.

In both market segments, banks display a strong preferential tendency to trade with partners based in their same country of origin.

6. Discussion and conclusions

Similarly to other exchange systems, markets turn transactions among participants into roles. These roles, in turn, reproduce resource flows in the face of uncertainty, and stabilize market exchange by decoupling the sides of transactions across time and settings. What mechanisms make this possible? What contingent conditions trigger or deactivate such mechanisms? These are the main questions that oriented our study.

Building on a progressive line of sociological research on markets developed during the last forty years (White, 1981a), we grounded this study in the observation that a defining characteristic of financial markets is that transactions and market roles are simultaneously determined. This happens because in financial markets the basic roles of “buyer” and “seller” do not precede, but *are contingent on* individual transactions. This constitutive feature of financial markets makes transactions themselves central to the understanding of market as concrete social structures (Aspers, 2011; Knorr-Cetina, 2004; White, 1988).

Taking this view as our starting point, the analytical strategy that we implemented in this study accords theoretical primacy to individual transactions in explaining how local structures in markets emerge and reproduce. Obviously we are not the first to note the analytical value of focusing on individual transactions to understand institutions (Williamson, 1981). However, we believe that our attempt to develop specific dependence hypotheses *linking transactions over time and across settings* provides new opportunities for testing our sociological understanding of markets using data that markets themselves routinely produce.

The focus of the empirical analysis has been on how the self-organizing dynamics of local structure varies across temporal and material contexts of exchange. We believe that the models for relational events that we have implemented are among the few available that are consistent with a theoretical view of "social structure" as a self-reproducing pattern discernible across multiple flows, rather than a "building "structure" static and dead" (Padgett, 2018, p.406). In this study, we tried to articulate this theoretical view that makes "time" and "structure" indissolubly intertwined.

We noted that their extreme level of role fluidity contributes to make financial markets inherently unstable as social exchange systems. Few institutional constraints preclude market participants from switching role suddenly and at the same time, thus amplifying fluctuations generated by uncertainty perceived about future resource availability. These fluctuations have obvious and concrete implications for the ability of markets to make the price of financial assets predictable. We argued that generalized exchange serves as a stabilizing function for financial markets by turning providers of resources into receivers through multiple overlapping chains of transactions. As a resource allocation mechanism, generalized exchange is valuable, but also fragile and unreliable (Yamagishi and Cook, 1993).

The presence of generalized exchange – and in fact of any kind of stable local structure – is surprising in a competitive impersonal market like the one we have examined. We have argued that the anti-hierarchical effects of cyclic closure are sustained by the coupling of role fluidity and shared constraints. All banks have reserve and liquidity constraint to satisfy. Any market participant may experience the need to sell or buy liquidity at any point in time to satisfy liquidity constraints. Hence market participants have a vested (individual) interest in ensuring that the market remains responsive to their contingent needs. But our study goes beyond the observation that the behavior of market participants may be shaped by the recognition of facing similar institutional and resource constraints. More specifically we asked: Under what *conditions* are financial transactions more likely to self-organize into cyclical relational event sequences with generalized exchange properties?

We addressed this question using data that we have collected on all the overnight transactions recorded in the European electronic market for interbank deposits (e-MID). The interpretation of market transactions as relational events connecting buyers and sellers of liquidity allowed us to link our conjectures about generalized exchange in financial markets to actual data on transactions that these markets routinely generate. We note, in passing, that models for social networks emphasizing state-transitions would not have afforded an adequate representation of very high-frequency, fast-clip, time-specific relational event data produced by financial transactions executed through an electronic market interface. Our attempt to link sequences of financial transactions to the emergence of generalized exchange was grounded in the view that: "The meaning of an event is conditional on its position in a sequence of interrelated events" (Bearman et al., 2002, p.61).

We found that generalized exchange in financial markets is more likely to emerge from sequences of transactions only in the longer term – and only in segments of the market dedicated to "regular" rather than "large" transactions. The former result is consistent with our argument about the implausibility of the – frequently implicit – assumption that social mechanisms operate instantaneously and timelessly. For example, in our sample the median time needed to observe cyclic closure of a two-path sequence – the micro-mechanism responsible for producing generalized exchange – was 87 days, almost three months. Generalized exchange is a cognitively complex social mechanisms that may only emerge over time through trial-and-error learning, and that is therefore likely to involve considerable perception delay. We think this result invites future research to probe deeper into the cognitive substrate of social mechanisms, and document how it affects the time needed for participants in exchange situations to learn the social structure that they themselves generate, and the consequences of its interaction with their own contingent interests. This results also invites future studies to acknowledge that network mechanisms need time to emerge. How long it takes, exactly, for specific network mechanisms to emerge and exercise a their effect on individual behavior are very reasonable questions that we are not yet prepared to address.

The latter result is consistent with the argument we developed about the incentive properties of generalized exchange, which has been repeatedly shown to be prone to free riding in experimental settings (Yamagishi and Cook, 1993) and simulation studies (Takahashi, 2000). In the empirical setting that we have examined, the risk inherent in opportunistic behavior makes generalized exchange work for regular overnight transactions, and fail for large overnight transactions. This result has to be interpreted in connection to the tendency of the market for large overnight transaction to take on a more hierarchical charter. The analysis reveals that the social structure induced by larger transactions is more hierarchical and involves more specialized roles, and a stronger tendency toward centralization. The diminished role fluidity determined by hierarchization is likely to weaken tendencies toward generalized exchange precisely because the crystallization of roles hinders the formation of collective expectations that "receivers" of funds may turn into "givers" of funds in the future. This may be one factor disabling generalized exchange as a social mechanism for controlling the risks of opportunism when the value of transactions increases.

More generally, the study suggests that future research on network mechanisms might benefit from a greater attention to variations in the details of institutional and organizational settings that make exchange concretely possible. The benefit would not be restricted to research on exchange behavior mediated by markets, but extend naturally to other institutional and technological interfaces designed to support coordination in large-scale social exchange systems. We think that the results of the study provide broader motivation for future empirical research to develop a richer and more detailed understanding of how the workings of otherwise generic network mechanisms vary subtly over time and temporal context, and across material conditions of exchange. Such an understanding is needed to improve our ability to predict when asymmetric exchange will be likely to emerge – and be sustainable – in complex adaptive social systems.

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