Social Networks 35 (2013) 130–143

Contents lists available at SciVerse ScienceDirect

Social Networks

journal homepage: www.elsevier.com/locate/socnet

# Extended structures of mediation: Re-examining brokerage in dynamic networks☆

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ARTICLE INFO

*Article history:*
Received 25 June 2012
Received in revised form 25 January 2013
Accepted 1 February 2013

*Keywords:*
Brokerage
Social processes
Structural theory
Social networks
Structural dynamics
Coordination
Emergent multi-organizational networks

ABSTRACT

In this paper we revisit the concept of *brokerage* in social networks. We elaborate on the concept of brokerage as a *process*, identifying three distinct classes of brokerage behavior. Based on this process model, we develop a framework for measuring brokerage opportunities in dynamic relational data. Using data on emergent inter-organizational collaborations, we employ the dynamic brokerage framework to examine the relationship between organizational attributes and coordination in the evolving network. Comparing the findings of our process-based definition with traditional, static approaches, we identify important dimensions of organizational action that would be missed by the latter approach.


## 1. Introduction

While much network research has emphasized the study of relationships that are stable over long periods of time (*e.g.*, kinship, close friendships), network scholars have also recognized the importance of accounting for the dynamics of social structure. Indeed, a dynamic intuition often lies behind overtly static modes of analysis, even when this intuition is not directly articulated (a point emphasized by Friedkin (1991) and Borgatti (2005)). For instance, Simmel (1949) famously argues that a triadic configuration is fundamentally different from a dyadic relation: the properties of the triad cannot be reduced to properties of the dyad. While this assertion is necessarily true in a strict structural sense (see *e.g.*, Mayhew, 1980), the Simmelian case for its sociological relevance is based not on the static structural differences between groups of different sizes, but on the differing potential of those groups for structural *change*. In particular, a key difference between dyadic and triadic groups is the possibility for competitive exclusion. With a triadic structure it is possible for any pair of actors to threaten to form a coalition, interacting with each other while excluding the third. By contrast, no such asymmetric threat can be made in a dyadic context, where excluding another from interaction means simultaneously abstaining from it oneself. From this point of view, it is the possibility for change in the structure—the credible threat of exclusion—that makes triads vital social structures with unique social characteristics (Simmel, 1949) and motivates their study.

Like Simmel, many social network researchers have built their work tacitly or explicitly on dynamic foundations; indeed, some have taken the underlying dynamics of social structure to be a defining assumption of the field (*e.g.*, Knoke and Yang, 2007, p. 6). Despite this long-standing theoretical appreciation, however, empirical and methodological developments within social network research have centered primarily on measurement and characterization of *static* network structures. While this restricted focus was understandable in an era in which dynamic network data were difficult or impossible to obtain, the increased availability of high-quality dynamic network data in recent years (due in part to developments in computer-assisted data collection and the emergence of online networks) has begun to challenge researchers to revisit their traditional approaches to data analysis. In particular, it is now practical in many situations to re-explore static network concepts and measures that were originally motivated by dynamic

☆ This material is based on research supported by the Office of Naval Research under award N00014-08-1-1015, as well as the National Science Foundation under awards CHE-0555125, BCS-0827027, CMMI-1031853, and OIA-1028394.

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http://dx.doi.org/10.1016/j.socnet.2013.02.001

processes, and to re-found them in a way that is true to the underlying theoretical assumptions. One such concept—and the one with which we shall concern ourselves here—is *brokerage*.

In its simplest terms, brokerage occurs when one actor serves as a bridge between two other actors who themselves lack a direct connection to one another. The concept of brokerage has been used in many different contexts, each of which has contributed to its formalization. However, while the act of brokerage is traditionally conceptualized as a dynamic phenomena, measures of brokerage have remained within the realm of static social relationships. In the following sections, we trace the development of these traditional measures in order to show how they fall short when applied in dynamic settings. This motivates our re-formulation of a *dynamic* measure of brokerage designed to capture and distinguished between three different classes of brokerage mechanisms important in the literature. The introduced measure is applied in a case study which clearly demonstrates its potential to offer a more nuanced characterization of relational sequences that constitute bridging opportunities in a dynamic relational structure, as well as potentially aid in causal inference about the relationship between brokerage acts and structural dynamics.

One common context for brokerage is the case of trade relations, in which economic actors may exchange with a limited number of alters. In such environments, those individuals, organizations, and political entities that were in a position to transfer goods from one location to another—and to control their dissemination—played a key role in sustaining trade at the regional and continental scales. By brokering contacts among distant third parties (who could not otherwise exchange with one another), these actors allowed critical, spatially localized resources to be deployed across large areas, thereby facilitating the growth of complex societies.[1] While brokerage in exchange networks has important systemic consequences, its individual-level effects have been more extensively appreciated by sociologists (see *e.g.*, Marsden, 1983; Gould, 1989; Burt, 1992). Actors who bridge those not otherwise connected have the potential to extract a portion of the value generated via the exchange, making brokerage a potentially profitable enterprise at the individual level. To the extent that this brokerage is exclusive (*i.e.*, no other brokers bridge the third parties in question) and involves redundant contacts on the part of the broker (*i.e.*, the broker can obtain the resource needed by one alter from multiple different alters), the brokering actor can additionally gain power in his or her individual transactions via the threat of competitive exclusion (Willer, 1999).[2] This intuition is powerfully illustrated by Burt's (1992) famous "structural hole" metaphor: by "filling the hole" between two parties, the broker not only connects them, but does so in a manner that may increase their dependence on the broker. In addition to advantages from power *per se*, brokers may also benefit from having direct and immediate access to a wider range of resources than those in other positions (a point also emphasized by, *e.g.*, Powell et al., 1996, 2005).

As the above suggests, exchange relations have been central to sociological theories of brokerage. It should be noted, however, that this is not the only context in which brokerage may occur. Obstfeld (2005) notes that brokers can serve to *create* ties, bringing together third parties not currently tied to one another (*i.e.*, "matchmaking"). This case is distinct from those discussed above, as the bridging position of the broker is only temporary, and gains accrue from the creation of a new relationship between the brokered parties (rather than the activity of the broker as conduit for information or resources). While matchmaking can occur in a pure exchange context, it may also take place in the context of other relationships (*e.g.*, friendship, romantic relationships) for which exchange of information or resources is of secondary importance. What is required for the viability of matchmaking is not resource misallocation, but positive value for ties with specific alters (or alter types), together with an inability of actors to form those ties on their own (either due to lack of information on available partners, or constraints on the tie formation process itself).

Ironically, yet another important context for brokerage is that in which edges have *negative* value (*i.e.*, ties are costly), but network connectivity *per se* is valuable. Here, a broker can serve to add value to his or her alters by bridging them to one another, without their having to maintain costly direct ties. This is particularly relevant in organizational settings, where management of dependencies (Thompson, 1967) is frequently a concern. Although dependencies can be resolved by multilateral negotiation, this is a costly strategy; instead, a core principle of organizational design is the aggregation of coordination functions into a relatively small number of actors, permitting others to focus on task performance (Galbraith, 1977). While traditionally conceived in terms of formal networks, the role of broker as coordinator has also been explored in emergent multi-organizational networks such as those arising during disaster response (Lind et al., 2008), in which both the need for coordination and the costs of direct interaction are high. By concentrating interaction costs on a relatively small number of organizations who broker contacts among a much larger set, coordination can in principle be maintained with minimal overhead.[3]

### 1.1. From position to process

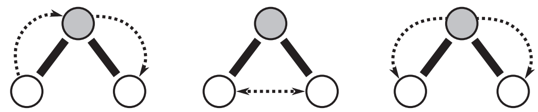
Clearly, brokerage may occur in many different settings, and the nature of the brokerage process itself varies substantially by context. At the same time, there are important unifying features both within and across the cases discussed above; we summarize these briefly in Fig. 1.[4] Broadly speaking, these brokerage processes fall into three classes: *transfer brokerage*, in which the broker (ego) conducts information or other resources from one alter to another who cannot be directly reached; *matchmaking brokerage*, in which ego introduces or otherwise makes possible a tie from one alter to another; and *coordination brokerage*, in which ego directs alters' actions so as to resolve their dependencies without need of direct contact. While all three classes involve the classic structural element of the incomplete (or "open") two-path—that is, a structural configuration in which one actor can reach another through an intermediary, but not via a direct tie—their mechanisms of mediation, preconditions, and effects are nonetheless distinct. As we discuss in greater detail below, traditional approaches to

[1] Indeed, the loss of such trade connections has been implicated in societal collapse (Tainter, 1990).

[2] Although Burt (1992) argues against redundant contacts, the lack thereof removes exclusion as a credible threat, and thereby the broker's dependence advantage (in the sense of Cook et al., 1983); as this phenomenon has been understood at least since Cournot's (1838 [1897]) foundational work on bilateral monopoly, it is surprising that it is not more widely known among sociologists (though see Willer, 1999).

[3] In the United States, this principle has been institutionalized in the Incident Command System (Auf der Heide, 1989), although its practical adequacy in large-scale disasters remains a matter of debate (see, *e.g.*, Wenger et al., 1990; Buck et al., 2006).

[4] It should be noted that we, following the majority of work in this area, define brokerage as a "relation involving three actors, two of whom are the actual parties to the transaction and one of whom is the intermediary or broker" (Gould and Fernandez, 1989, p. 91). This definition implies that a brokerage opportunity can be identified by considering the triplet of actors and the relations among them, *i.e.*, the induced subgraph or triad. In the subsequent discussion and in our dynamic formulation of brokerage we follow this convention. Indeed this basic notion of brokerage has formed the foundation for numerous extensions to basic brokerage behavior that consider the larger structural context in which the brokerage relation is embedded (see *e.g.*, Krackhardt, 1999; Tortoriello and Krackhardt, 2010). While these cases are important for their sociological relevance they are beyond the scope of this paper.



| | **Transfer** | **Matchmaking** | **Coordination** |
|---|---|---|---|
| Broker generates value by... | Conducting resources from one party to another | Facilitating tie formation between third parties | Allowing third parties to act without creating a direct relationship |
| Third-party tie is inherently... | Infeasible | Valuable | Costly |
| Mechanism of mediation | Resource held by first alter is transferred to second | First alter is introduced to or allowed to form tie with second | Dependencies from first alter used to guide second |
| Effect of brokerage on potential third-party tie | None (direct tie infeasible) | Increased chance of formation | Decreased chance of formation |

**Fig. 1.** Three classes of brokerage mechanisms; solid edges reflect primary relationships between ego (grey) and alters (white), while dotted edges indicate core process elements.

brokerage analysis (*e.g.*, Gould and Fernandez, 1989) center on identifying incomplete two-paths, and as such capture the configuration that is common to all forms of brokerage. This emphasis has served as a useful conceptual move, in the sense that it has allowed brokerage opportunities to be assessed in a way that is agnostic to the specific process involved. This generality has come with a price, however. By focusing only on two-path structure, the traditional approach is unable to distinguish between competing processes, or to evaluate their empirical consequences (for example, matchmaking and coordination processes have very different consequences for subsequent edge formation between the third parties involved). Perhaps more significantly, such an approach becomes problematic in the presence of structural dynamics, where an accounting of brokerage opportunities is impossible without a more precise specification of *how* brokerage unfolds over time (*i.e.*, the brokerage *process*).

The need for an explicitly dynamic treatment of the structural conditions facilitating brokerage is clear when we consider the mechanisms of mediation summarized in Fig. 1. In the case of transfer brokerage, for instance, brokerage constitutes the transfer of some resource (*e.g.*, information or physical goods) from an alter ($a$) to ego, followed at some later time by the transfer of this resource (or a fraction thereof) from ego to a second alter ($b$). In an effectively static structural context—*i.e.*, where the network of possible interaction partners changes slowly compared to the pace of interaction—the presence of an open two-path from $a$ to $b$ containing ego is adequate to characterize the brokerage condition. Where network structure evolves on a time scale comparable to interaction, however, this condition is insufficient: for alter $a$ to send a resource to alter $b$ via ego, the contacts between $a$ and ego and $b$ and ego (respectively) must not only occur, but must occur in the correct temporal order. Likewise, the condition that $a$ and $b$ cannot transact directly (a precondition for the need to resort to mediated transfer in the first place) must be sustained during the period in question; if $a$ and $b$ find themselves able to transact before ego can broker their interaction, it seems reasonable to posit that they will do so. Consideration of the unfolding dynamics of the brokerage process thus places corresponding constraints on the dynamics of the network that is to support it, just as consideration of the time-aggregated aspects of this process lead to the recognition of the importance of two-paths in the static case.

It is interesting to note that, for all three of the process classes considered here, this basic temporal logic ($a$ tied to ego, followed by $b$ tied to ego, without an intervening tie from $a$ to $b$) defines the critical necessary condition for the performance of brokerage. As such, it is a natural starting point for the identification of brokerage opportunities within evolving networks (a matter that we will presently consider in greater detail). There are, however, differences between the classes that become apparent in the dynamic context. For instance, in the case of matchmaking brokerage, it is clear that the order of contacts (*i.e.*, whether $a$ or $b$ is the first to encounter ego) will matter only when there are special constraints on which alter can initiate their direct interaction (*e.g.*, marriage in cultures with gendered proposal rules). Otherwise, the process exhibits a *temporal symmetry* generally lacked by the transfer process (in which starting and ending points are distinct). This property is partially shared by the class of coordination brokerage processes, in the sense that dependencies can often be managed either by adjusting the activities of $a$ to conform to the dependencies of $b$, or vice versa. Nevertheless, the manner in which dependencies are resolved by ego (and the success with which this can be performed in practice) may depend upon the order in which contacts are made, and hence the order of contacts is potentially meaningful in some circumstances.

Another difference between the brokerage process classes is in the effect of the act of brokerage on the evolving network itself. In the transfer case, the very rationale for brokerage is the lack of a direct contact between alters; classically, it has been assumed that establishing such contact is infeasible on the time scale of interaction, and hence that brokerage has no short-term impact on the underlying network itself.[5] Such an assumption is obviously inappropriate in the case of matchmaking brokerage, which is predicated on the notion that ego's brokerage of $a$ and $b$ will encourage the formation of a direct tie between them. Successful matchmaking brokerage, then, will be associated with the elaboration of our base tie sequence ($a$ to ego, then ego to $b$) with a direct tie between $a$ and $b$ that occurs after the base sequence has taken place.[6] By turns, the implicit source of value in the case of coordination brokerage is the avoidance of a direct tie from $a$ to $b$—thus, successful brokerage here should *inhibit* subsequent direct contact.

These basic observations can be stated more formally using the language of *dynamic network analysis*, the intertemporal counterpart to the familiar framework of classical social network analysis (Wasserman and Faust, 1994). Such formalization allows us to move from theoretical intuitions regarding structural processes to

[5] Burt (1992) argues that brokerage incentives will lead some actors—dubbed "entrepreneurs"—to form bridging ties, but this is implicitly assumed to occur on a time scale much longer than any single interaction. See also Buskens and van de Rijt (2008) on the complications arising from a relaxation of this assumption.

[6] Unsuccessful matchmaking requires only the base sequence, of course.

specific measures on dynamic networks, just as classical network analysis has allowed scholars to move from intuitions regarding social position to measures of static network structure. Although many familiar network analytic notions carry forward from the static case to the dynamic, others do not (as clearly articulated by Moody (2002) in the context of connectedness and diffusion; see also Butts (2009)). Given appropriately derived dynamic measures of brokerage opportunity, we can assess the extent to which evolving networks allow some actors rather than others the ability to engage in transfer, matchmaking, or coordination brokerage. In the latter cases, we can also gauge the success of these efforts, at least in the sense of whether direct ties were either created or inhibited as expected. In the section that follows, we pursue this problem in greater detail, combining the theoretical developments of this section with classical tools of brokerage measurement to generate a new approach to the assessment of brokerage processes in dynamic networks. Subsequent sections of the paper apply this new approach to a case study of emergent networks formed in response to the Hurricane Katrina disaster, and assess the extent to which the resulting findings differ from what could be inferred from the classical (static) approach.

## 2. From process to practice: formalizing brokerage

Although we have identified several key facets of the brokerage process, applying these to empirical data on dynamic interaction requires a formalization of the associated framework. Rather than starting this process *ex nihilo*, we begin by re-assessing the classical formalization of brokerage as a structural position, with an eye to its relationship to the view of brokerage as process. From this beginning, we construct a new framework which accommodates the process-oriented view, but which retains the insights of the classical approach. Following the approach of Mayhew (1984) and others, we then derive a family of baseline models for dynamic brokerage that can be used as benchmarks to assess the presence of structural biases in brokerage opportunity. These baseline models are employed in the subsequent portion of the paper, in which we evaluate the determinants of brokerage in an emergent multi-organizational network.

### *2.1. The classical approach*

The canonical view of brokerage (*e.g.*, Gould and Fernandez, 1989; Burt, 1992) is one of a set of actors embedded within an effectively static network (*i.e.*, fixed over the time scale of interaction) of potential partners, with exchange dynamics treated as an unobserved process carried out within the constraints of the underlying network. Primary theoretical emphasis is then placed on the structural conditions conducive to the development and exercise of power (broadly defined) (see, *e.g.*, Cook and Emerson, 1978; Cook et al., 1983; Burt, 1992; Willer, 1999). In particular, the ability to *exclude* actors[7] is identified as an important structural basis of power, as originally recognized by both Marx and Weber (see Willer, 1999 for a discussion and review). Similar ideas are found in traditional economic models of exchange, such as in classic Bertrand competition. A number of elaborate—and predictively successful—theories have arisen to explain the detailed relationship between structural position and power (or other exchange outcomes), a research program that continues to the present day. (See Willer and Emanuelson (2008) for a recent comparative review.) While the prediction of power within complex networks is difficult, theorists in the field have long noted that powerful positions tend to arise in circumstances in which a single ego has ties to multiple alters who are not themselves able to trade with one another.[8] These brokerage "positions" are thus expected (*ceteris paribus*) to be associated with the ability to exercise power, and hence with above-average payoffs. Despite these roots, this "classical" view does not reflect a fixed, primordial conception of power in exchange, but rather evolved from a combination of theoretical and empirical efforts stemming from early work such as that of Blau (1964), Coleman (1972), Emerson (1976), and Homans (1961). While early work focused primarily on interaction in dyadic settings, this perspective gradually broadened to incorporate exchanges contained within a larger, more complex relational structure, a move made feasible by considerable advances in the study of social networks (see, *e.g.*, Cook et al., 1983; Bonacich, 1987; Markovsky et al., 1988, for examples of this interchange). The resulting recognition of the importance of mediating positions for power exercise—and the ability to treat this concept in a formal manner—was thus a major advance over earlier, less structurally contextualized work.

Another conceptual advance of this era was the formalization of *social roles* and *positions* in terms of principles of equivalence (Lorrain and White, 1971; White and Reitz, 1983; Everett, 1985). Rather than describing roles and positions in terms of functional characteristics, it became possible to describe them via their relational properties (allowing the position or role to be both inferred from and generalized from the specific case). Recognizing the importance of mediation from both the above-mentioned exchange work and from a long tradition of interest in the literature on centrality and information flow (*e.g.*, Shimbel, 1953; Granovetter, 1973; Freeman, 1979), Gould and Fernandez (1989) introduced a formal definition of the *brokerage role* as a general family of structural positions. A more specialized notion than the equivalence-based role concepts, the brokerage role narrowly identifies the core structural feature associated with brokerage in its classical sense (*i.e.*, the ego who bridges two alters). At the same time, Gould and Fernandez expanded upon then-existing concepts of brokerage to include contextual factors stemming from the properties of the actors within the role,[9] leading to a fivefold typology of brokerage roles. Although the structural properties captured by the Gould–Fernandez (henceforth G–F) scheme were not novel, their approach made three important advances: (1) it provided a clear way to quantify the presence of brokerage opportunities within fixed networks; (2) it set forth a systematic approach for distinguishing among brokerage-related positions by the properties of the actors involved; and (3) it provided an abstract, fully structural concept of "brokerage" that could be applied in general settings. Although the present work could be construed as a reaction to this last advance, we do not wish to undermine its importance in the original context. Had brokerage not been liberated from the narrow setting of exchange, its broader applicability would have been significantly obscured.

The five types of brokerage roles identified by Gould and Fernandez (1989) that can arise in a directed network are depicted in Fig. 2. The first, called *coordinator* brokerage by G–F (and not to be confused with the coordination brokerage process of Fig. 1),

[7] Following the bulk of the literature in this area, we focus here on *negative* exchange networks, in which actors have competing interests (see, *e.g.*, Cook et al., 1983). Certain types of brokerage processes (*e.g.*, matchmaking) may also serve an important role in *positive* exchange networks, but this has not been a major concern of the classical, position-oriented view of brokerage.

[8] In the most extreme case of an ego with multiple pendant alters (a star configuration), in fact, ego's power is generally maximized.

[9] Gould and Fernandez (1989) refer to these properties in terms of subgroup memberships, but their formalism incorporates any categorical attribute, covariate, or exogenous structural position (*e.g.*, social category membership) which can be treated as "fixed" with respect to the brokerage role itself.

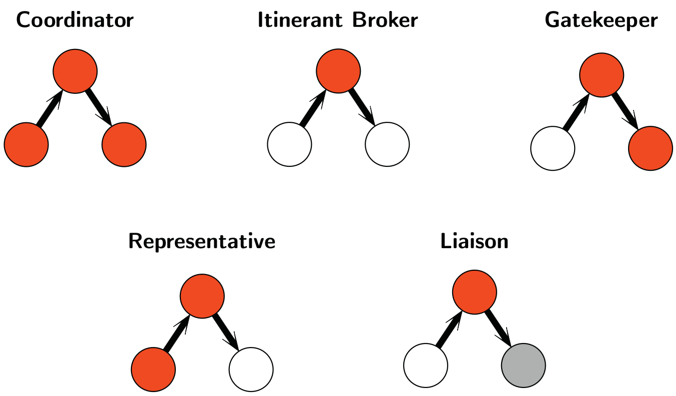



**Fig. 2.** Illustration of the five Gould–Fernandez brokerage roles in a directed network.

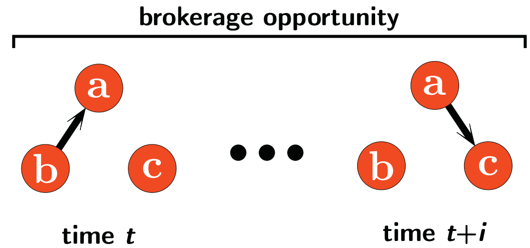



**Fig. 3.** Brokerage opportunity across multiple time points.

occurs when all three actors belong to the same affiliation subgroup or class. The G–F term for this role is intended to suggest the intuitive notion of a coordinator as an internal group member chosen to coordinate activities, although it should be noted that the definition is purely positional and does not relate to the nature of the process by which brokerage is carried out. The second type of brokerage role occurs when the two alters belong to the same subgroup, but the broker belongs to a different subgroup. This type of brokerage is called *itinerant* brokerage by G–F. The third and fourth types of brokerage roles are referred to by G–F as *gatekeeper* and *representative* brokerage, respectively. The last type for brokerage is called *liaison* brokerage. This type of brokerage occurs when all three actors involved are affiliated with different subgroups. These five distinct brokerage roles constitute a complete enumeration of the possible distinctions to be made for an ego sitting on a directed path between two non-adjacent alters, on the basis of categorical properties of ego and/or the alters. Following G–F, we refer to coordinator and itinerant brokerage roles as *within* group roles because the two alters are affiliated with the same class or subgroup. Similarly, gatekeeper, representative, and liaison brokerage are considered *between* group brokerage roles.

The five brokerage types illustrated in Fig. 2 represent distinct social roles, encapsulating an elementary aspect of an actor's structural position within a given network. Recognizing that a given individual may occupy a brokerage position *vis-à-vis* multiple pairs of alters, G–F quantify the overall participation of individuals in brokerage roles via a *brokerage score*. G–F formally define brokerage in a graph representing the non-symmetric binary relation $R$; $a$ is said to broker between $b$ and $c$ if and only if $bRa$, $aRc$, and $b\bar{R}c$, where $bRa$ indicates that $b$ is tied to $a$ by the relation $R$, and $b\bar{R}c$ is the negation of $bRc$. With this definition, brokerage scores are calculated by counting the number of times the above condition holds for specific combinations of actors' affiliations. Stated less formally, this means that if some actor $x$ occupies the position of coordinator broker twice and representative broker three times, that actor would receive a coordinator brokerage score of two, a representative brokerage score of three, and a total brokerage score of five.

The G–F brokerage scores capture the essence of the classical view of brokerage. As a static positional measure, a G–F brokerage score summarizes the role of ego as a potential bridge, with the process of action left tacit. Likewise, this bridging potential is assumed based on the implied simultaneity of edges within the network: ties among actors (and the actors themselves) are assumed to remain fixed over the time scale of action. When we relax the assumption of stasis, however, it can be seen that the classical view encounters difficulty, having no way to deal with the order in which relationships transpire, much less the appearance or disappearance of individual actors. Likewise, the strong process agnosticism of classical brokerage does not allow us to distinguish between transfer, matchmaking, or coordination brokerage (even on a structural basis). We must therefore go beyond the classical formalization of brokerage in order to incorporate structural change, a task to which we now turn.

### 2.2. The process perspective

While social structure often displays considerable stability, this is far from universal. Relationships in certain settings (*e.g.*, emergent collaboration networks (Topper and Carley, 1999; Powell et al., 2005) or online citation networks (Adamic and Glance, 2005; Butts and Cross, 2009)) may change within hours or days, informal interaction patterns vary over periods of weeks or months (Newcomb, 1961; Johnson et al., 2003), and even close-knit friendships and kinship evolve on decadal scales (Suitor and Keeton, 1997).[10] Where brokerage unfolds on time scales comparable to the period of relational change, failure to consider structural dynamics may lead to a substantially flawed understanding of the brokerage process. More importantly, brokerage processes such as matchmaking and coordination are intrinsically related to structural dynamics, and hence cannot be captured within a static framework. With this in mind, we require a formalization of brokerage that explicitly incorporates such change. At the same time, it is important to incorporate the insights of the classical formulation, constructing a process variant that preserves the key properties of the original. We thus proceed by starting with the classical formalization, and examining its behavior in a dynamic network context; our emphasis is on identifying a minimal set of changes that will bring the behavior of the formalism in line with the properties of the brokerage process, as outlined earlier in the paper. With this result in hand, we will be left with a specific framework for assessing brokerage opportunity in dynamic settings, just as the G–F brokerage roles allow for an assessment of brokerage potential in the static case.

While the simultaneous tie structures of Fig. 2 continue to imply brokerage opportunity in the dynamic case, there are also tie sequences that are consistent with brokerage opportunity, but which do not include a two-path structure in any single temporal cross-section. For instance, Fig. 3 depicts a minimal case in which node $a$ has the opportunity to broker between nodes $b$ and $c$, but this opportunity can only be seen by observing multiple time steps. For instance, in the case of transfer brokerage, node $b$ has the opportunity at time $t$ to pass information or resources to node $a$, which could then potentially be passed on to node $c$ at time $t+i$. In the absence of a known time horizon for the expiration of the transfer opportunity, we place no *a priori* restrictions on the length of time

[10] Indeed, many micro-interactions unfold over such narrow time scales that we do not think of them as forming "social structures" in an enduring sense, although they nevertheless have important structural dimensions (Gibson, 2003; McFarland, 2001); see *e.g.*, Butts (2008) for a discussion of relational time scales and their implications for choice of representation.

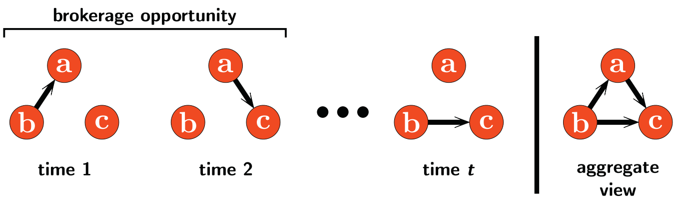



**Fig. 4.** Illustration of sequential brokerage. Times 1 through $t$ aggregated would appear as the last element of the figure (labeled "aggregate view"). A brokerage opportunity exists from the start of time 2 until time $t$, at which point the triad closes.

over which such a brokerage opportunity may occur.[11] However, recall that G–F restrict their definition of brokerage by disallowing the tie between the brokered alters (here, nodes $b$ and $c$). Consistent with this intuition, we also require the non-existence of this $b \rightarrow c$ edge between the initialization of the opportunity at time $t$ and its completion at time $t+i$. This simple formulation implements the logic of the common thread identified in our earlier discussion of brokerage process: for all forms of brokerage, we require the opportunity for a connection between $b$ and $a$, followed by an opportunity for a connection between $a$ and $c$, with no intervening opportunity for direct interaction between $b$ and $c$.

Careful examination of the preceding case reveals that our initial description of dynamic brokerage may coincide with that obtained by the G–F brokerage role as applied to the time-aggregated (but not *cross-sectional*) network structure. In the case where the $b \rightarrow c$ edge never exists, both the static formulation as applied to the time-aggregated network and the dynamic formulation would capture the same structural roles; this is true because, in this specific case, the incomplete triad condition is maintained throughout the interaction history. Such a coincidence need not occur. Consider, for instance, the aggregate network appearing on the right-hand side of Fig. 4. In a classical analysis, the $b \rightarrow c$ edge is seen as closing the triad, thus preventing $a$ from acting as a broker between $b$ and $c$. When such a pattern arises from a time-aggregated structure, however, we cannot infer that node $a$ lacked the opportunity to act as a broker between nodes $b$ and $c$. Indeed, the relational history on the left-hand side of Fig. 4 reveals that the $b \rightarrow c$ edge appears only *after* the $b \rightarrow a$, $a \rightarrow c$ sequence was already complete (a pattern characteristic of matchmaking). What appears in the aggregate view as a closed triad was actually one in which $a$ had the opportunity to act as a broker for $b$ and $c$.

Fig. 4 illustrates a situation that the classical view of brokerage is not equipped to handle, and which we may readily expect to occur (*e.g.*, in the context of matchmaking). In the case of truly directional interaction, we may also obtain discrepancies due to the order in which the $b \rightarrow a$ and $a \rightarrow c$ edges occur: *e.g.*, in the case of transfer brokerage, if $b$'s opportunity to transfer goods to $a$ does not precede $a$'s opportunity to transfer goods to $c$, then $a$ is obviously unable to broker a transfer of resources from $b$ to $c$. In this case, a simplistic time-aggregate analysis would commit the opposite error of that in Fig. 4, falsely identifying a brokerage opportunity when none is present. Employing a static analysis in the dynamic case can thus result in both false positive (identifying brokerage opportunities where none are present) and false negative errors (missed brokerage opportunities), and does not supply an upper or lower bound on the number of brokerage opportunities within the evolving network. An explicitly dynamic treatment is required to obtain an accurate accounting.

With the above in mind, we formally define a dynamic analog to the brokerage role of Gould and Fernandez, extending the notation from Gould and Fernandez (1989).

**Definition 1.** In a graph representing a nonsymmetric binary relation $R$, $a$ is said to be a *dynamic broker* for $b$ and $c$ if and only if

$$(bRa)_t, (aRc)_{t+i}, \quad and \quad (b\bar{R}c)_{\forall t' : t < t' < t+i}$$

where $(bRa)_t$ indicates that $b$ sends a tie to $a$ at time $t$ by the relation $R$, and $(b\bar{R}c)_{\forall t' : t < t' < t+i}$ is the negation of $(bRc)$ for all $t'$ such that $t < t' < t+i$.

In other words, we require the tie between $b$ and $c$ to be absent for all time points between the initial tie from $b$ to $a$ and the subsequent tie from $a$ to $c$, completing the brokerage opportunity. Following Gould and Fernandez (1989), we denote the statement that $a$ brokers the $b$, $c$ relationship—in this case, a temporally extensive position that spans from time $t$ to time $t+i$—as $bac_{[t,t+i]}$. With this definition of dynamic brokerage, we may express the total dynamic brokerage activity of actor $j$ as the number of ordered pairs ($b$, $c$) and distinct time periods for which the condition $bac_{[t,t+i]}$ holds. Likewise, we can apply the fivefold G–F typology to the dynamic case, separately counting instances of brokerage positions that fall into each of the categories illustrated in Fig. 2. In analogy with the classical case, we describe the number of brokerage instances in each type for a given ego as his or her *dynamic brokerage score*, the vector of which provides a succinct description of the overall pattern of brokerage opportunities available to ego during the time period of observation.[12]

Before considering an empirical application of this dynamic brokerage concept, we briefly discuss some basic issues related to inference. As G–F note in the context of static brokerage scores, the problem with employing simple counts of brokerage opportunities as evidence of non-trivial social processes is that their values depend on the size and density of the network under consideration and the mixture of available node attributes. It is thus useful to consider simple models that can serve as reasonable "yardsticks" against which to compare observed brokerage scores, in the same manner as the standard models used in classical null hypothesis testing. With this in mind, we briefly turn to the problem of developing baseline models for the evaluation of dynamic brokerage scores.

### 2.3. Baseline models for dynamic brokerage

It is fairly straightforward to perform a complete count of brokerage opportunities for each actor in a network. However, simply reporting a count of observed occupancy in positions of brokerage is not enough; to be interpreted, this count must be

[11] A similar intuition about brokerage appears in the RSiena software (Ripley et al., 2012). Their "betweenness effect" is defined on three vertices ($j$, $i$, and $h$) observed at two times, $W$ and $X$, respectively, such that $j \overset{W}{\rightsquigarrow} h$ and $j \overset{W}{\rightarrow} i$, followed by $i \overset{X}{\rightarrow} h$. This captures a dynamic intuition of brokerage, but differs from our approach in two important ways. First, we keep with the original G–F intuition of brokerage by including the simultaneous tie structures of Fig. 2 as valid in our dynamic extension of brokerage, whereas the RSiena approach does not. Second, the RSiena approach stipulates $j \overset{W}{\rightsquigarrow} h$ but not $j \overset{X}{\rightsquigarrow} h$, whereas in Definition 1 we require the absence of the closing third tie for *all* time points between the initiation and completion of the two-path. The RSiena approach makes it possible for $j \overset{X}{\rightarrow} h$ and $i \overset{X}{\rightarrow} h$, but this prohibits knowing whether the opportunity for $i$ to broker between $j$ and $h$ occurred prior to the formation of $j \rightarrow h$.

[12] By considering the overall pattern of brokerage opportunities during the time period of observation we are characterizing each actor's potential for participation in the brokerage process. This is not the only way to consider brokerage opportunity in a dynamic context; for example, we could consider a comparison of scores for two distinct time intervals. However, this is a succinct and straightforward way in which to explore brokerage opportunity in a dynamic context and allows for overall characterization of brokerage behavior.

compared to what would be expected to result from the low-level properties of the network at hand (*e.g.*, the number and types of actors, the number of relationships among actors). In the parlance of conventional sociological methodology, we wish to be able to determine when the observed brokerage score for a given actor is significantly greater than would be expected by chance given some reasonable null model (see *e.g.*, Mayhew, 1984, for a discussion of baseline modeling). In their initial work, Gould and Fernandez (1989) outline simple procedures for constructing baseline models of brokerage role incidence, against which observed brokerage scores can be tested. Many of these models were based on homogeneous Bernoulli graphs, in which all edges appear independently with equal probability. Although we regard the Bernoulli baseline as useful, we note that it preserves few aspects of the data, and thus does not constitute a very conservative test of brokerage roles (especially in the dynamic case). We therefore depart somewhat from the G–F scheme, instead drawing on permutation-based procedures (Hubert, 1987) to construct baseline models for dynamic brokerage scores.

Permutation-based procedures for constructing baseline distributions are widely used within the field of social network analysis in part because of their appealing substantive interpretation, as well as their robustness to dependence within the input data—an important aspect in contexts with complex relational dependency, like social networks (Krackhardt, 1987; Butts, 2007; Dekker et al., 2007). Network permutation models preserve the network *structure* while allowing individual actors to vary in the specific structural roles they occupy. By design this family of models is fairly restrictive, positing that the statistics of interest (here, brokerage scores) are adequately explained by the overall structure of the network. It is this family of permutation-based null models that we utilize to assess the significance of brokerage opportunities in the empirical case study presented subsequently.

## 3. A case study of brokerage role occupancy

While the preceding discussion of brokerage motivates the development of a dynamic formalization, an empirical application demonstrates the specific insights, both theoretical and practical, to be gained by such a formalization. Herein we examine brokerage opportunities within a network of organizational collaboration during the 2005 Hurricane Katrina disaster in the United States. The Katrina case provides a particularly relevant context in which to study brokerage because of the disruption of everyday channels of communication, mobility, and information access that resulted from the storm, and which is common in such disaster settings (Comfort and Haas, 2006). Brokerage processes thus become vital to the success of response and recovery activities.

Response efforts in a disaster setting typically involve a diverse set of actors working in close proximity, often on related tasks, amid a highly disrupted context (Comfort and Kapucu, 2006; Auf der Heide, 1989). Coordination among the actors, despite disrupted communication channels and infrastructure, requires the emergence of specific structural and situational roles. In a disaster setting, direct communication and coordination between organizations may be difficult, if not impossible, and the need for brokers to facilitate the flow of information and physical goods will likely be high (Marsden and Lin, 1982). Despite the vital role of brokers in such settings, the study of brokerage in networks of collaboration and communication in the context of disaster has not been fully explored within the sociological literature (see, however, Lind et al., 2008). This context provides a unique opportunity not only to demonstrate the proposed dynamic model of brokerage but also to highlight the differences between our approach and the classical, static conception of brokerage in a context of considerable substantive importance.

### 3.1. The data: inter-organizational collaboration

To illustrate our dynamic extension of brokerage, we make use of data that describes the emergent multi-organizational network (EMON) of collaboration activity among organizations involved in the initial response to Hurricane Katrina (Butts et al., 2012). These network data consist of 1577 organizations and the 857 collaboration ties among them, as coded from source materials collected from a large corpus of online documents. The class of source materials (called situation reports, or SITREPs[13]) from which these data were extracted are typically produced and distributed by various agencies and organizations, and are often updated frequently (often daily, at least) in the time before, during, and after a disaster. Within these data, an "organization" was defined as "any named entity which represents (directly or indirectly) multiple persons or other entities, and which acts as a *de facto* decision making unit within the context of the response." Ties of collaboration exist between pairs of organizations in this context "if they engage in any substantive interaction—*e.g.*, information transfer, exchange of manpower, donations of material or financial support, or delegation of authority—related to task performance" (Butts et al., 2012). Thus, the resulting organizational collaboration network consists of organizational responders and the reported collaborations between those responders. All network ties in these data are undirected since collaboration, as defined, is a reciprocal relation.

These Katrina EMON data track all of the inter-organizational collaboration activity associated with Katrina (and the earlier stages of the storm before it was named as such) up to and including the first seven days after landfall in Louisiana. The Katrina data are organized in several different ways, but for our purposes, we utilize two particular configurations of the data. One contains 13 daily "snapshots" of the network as it appeared on any given day, while the other represents an aggregated version of the network. In addition to the structural aspects of these data, a rich inventory of individual organizational attributes is included. For additional details about these data, their collection, and coding, see Butts et al. (2012).

### 3.2. Gould and Fernandez brokerage in the Katrina EMON

So that we may establish a comparison case to evaluate our dynamic extension of the brokerage measure, we apply the original G–F measure of brokerage to these Katrina EMON data. Specifically, we compute brokerage counts on the aggregated version of the Katrina network. The G–F measure, therefore, identifies structural opportunities for brokerage which may or may not be preserved in the process-oriented approach, as discussed in our theoretical treatment of this topic.[14] Recall G–F describe five distinct types of brokerage that result from a partition of the actors into distinct subgroups. By exploiting available organizational attribute information in these data, we partition organizations in the Katrina EMON using a combination of actor-level characteristics.[15] The result is the seven category classification given in Table 1.

[13] SITREPs are a mechanism for rapidly summarizing the current response situation; they include information about environmental conditions, hazards, losses incurred, and tasks being performed by organizations and individuals involved in the response (Butts et al., 2012). The specific documents that led to these Katrina EMON data were publicly accessible throughout the United States at the time of data collection. All available documents were gathered through multiple waves of data collection over the course of several months after the landfall and passage of Katrina. SITREPs typically follow a somewhat standardized template, allowing for relatively straightforward extraction of relevant relational information.

[14] It should be emphasized that this approach, which ignores detailed dynamic information, has historically been the standard course of practice for measuring brokerage in networks.

[15] Organizations are first divided into three categories based on their organizational type (Butts et al., 2012) The three categories of organizational types chosen

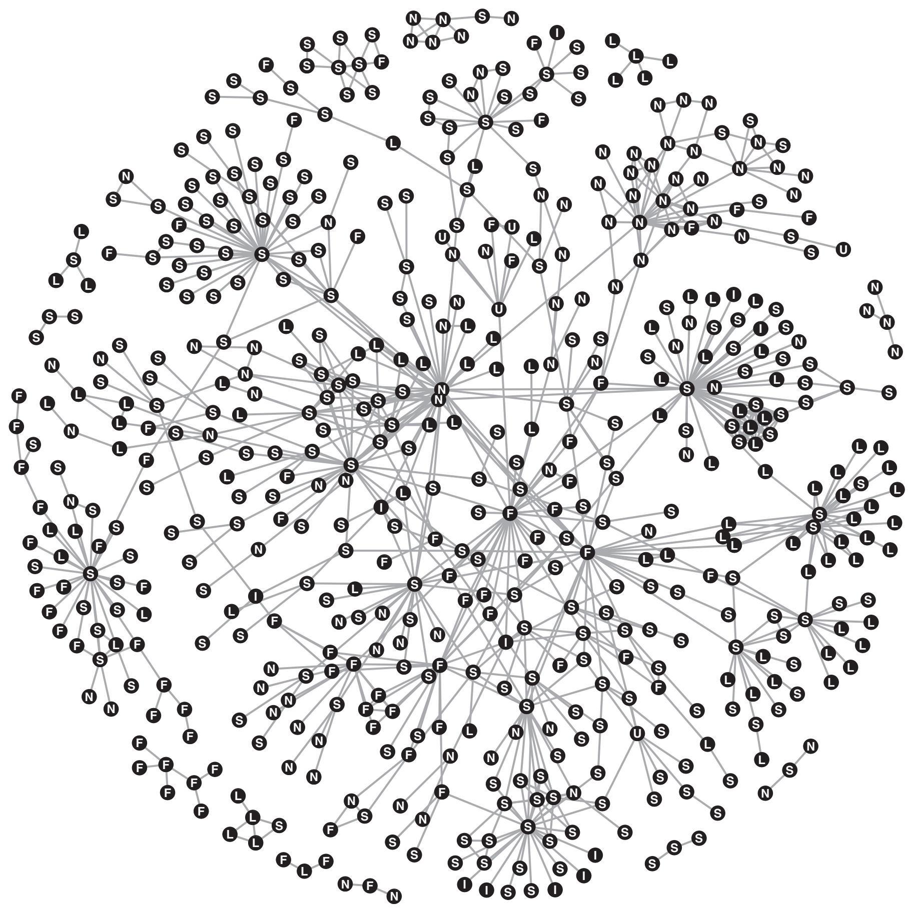


**Fig. 5.** Katrina collaboration network of brokerage opportunities. Vertex labels correspond to organizational subgroup memberships: federal (F), state (S), local (L), NGO (N), international (I), and unknown (U).

**Table 1**
Subgroup partitioning for Katrina EMON.

| | Subgroup | Number of organizations |
|---|---|---|
| 1. | Non-governmental (NGO) | 520 |
| 2. | State | 498 |
| 3. | Local | 272 |
| 4. | Federal | 220 |
| 5. | Gov't type unknown | 41 |
| 6. | International | 23 |
| 7. | Gov't with unknown scale | 3 |

Network visualization is one method for gaining basic insight into the relation under study. Fig. 5 represents a network subset of the aggregated version of the Katrina EMON in which all isolate and pendant organizations (and their associated ties of collaboration) have been omitted. These omissions allow one to more easily see which organizations are in positions of brokerage and which are third parties to brokerage configurations.[16] In Fig. 5, one will notice the presence of several star-like configurations. Organizations at the center of a star-like structure occupy positions high in brokerage potential. One also finds evidence of differential tendencies for mixing based on organizational subgroup affiliation. Overall, we can see that organizations in the Katrina EMON occupy a variety of potential brokerage roles.

The G–F formalization of brokerage roles is defined for networks in which relations are directed (*i.e.*, relations for which one makes a distinction between the sender and the receiver). Generalizing to undirected network data is relatively straightforward; with such data, each edge is treated as bidirectional. However, this introduces one important change to the original G–F formalization: in the case of undirected relations, one cannot distinguish a *gatekeeper* brokerage role from a *representative* role, since the absence of relation directionality reduces the two roles to one (in the case of undirected

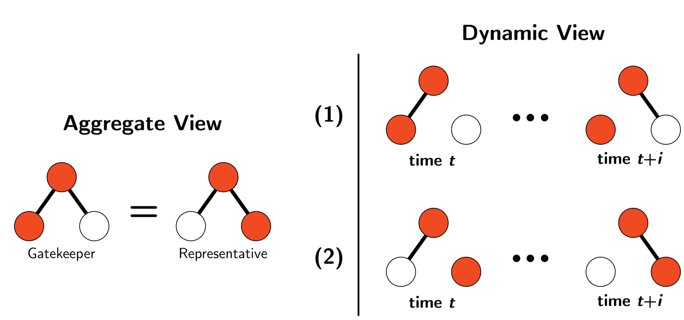



**Fig. 6.** Distinguishing gatekeeper from representative brokerage in the undirected case.

here are government, non-government organizations (which includes collective, not-for-profit, and for-profit organizations—collectively referred to as *NGOs*), and those whose type is unknown. We further subdivide government organizations into five different categories based on the scale of their operations: federal, state, local, international, and unknown scale. This strategy was motivated by our desire to emulate the subgroup membership categories of Lind et al. (2008).

[16] Any actor with either zero or one tie *cannot* be part of a brokerage relation.

**Table 2**
Subgroup memberships of brokers in the Katrina EMON. Values obtained from the static brokerage measure are given in non-shaded cells, and those from our dynamic measure are given in shaded cells.

| Subgroup | Brokers | | Prob. brokering given subgroup | |
|---|---|---|---|---|
| State | 102 | 109 | 0.20 | 0.13 |
| Federal | 26 | 29 | 0.12 | 0.13 |
| Unknown | 3 | 3 | 0.09 | 0.09 |
| International | 2 | 2 | 0.07 | 0.07 |
| NGO | 36 | 38 | 0.07 | 0.07 |
| Local | 19 | 23 | 0.07 | 0.08 |

relations, they are simply "mirror images" of each other, as seen in the "aggregate view" side of Fig. 6). In undirected networks, brokerage scores for these two roles will be identical.[17] As the Katrina EMON data contain information about *undirected* ties of collaboration, we make use of this generalized measure in the analysis that follows.

Under the G–F measure, 88 out of the 1577 organizations in the aggregate Katrina EMON are identified as brokers (about 12% of the organizations). The distribution of these organizations by subgroup affiliation, along with the probability of an organization occupying a position of brokerage given its organizational category, is given in Table 2. The seventh subgroup category (government organizations with unknown scale) is omitted since no organizations in that subgroup were identified as brokers in the aggregated Katrina EMON. These brokerage counts indicate that state organizations occupy a large portion of brokerage roles in the network.

Table 3 lists the top ten organizations in the Katrina EMON ranked by their total brokerage score, as identified by the G–F measure. All of the top ten brokering organizations have scores that are significantly high across all types of brokerage, though individual organizations show differential tendencies for specific brokerage roles over others. (Recall significance scores are determined using network permutation models.) Although three different organizational subgroup affiliations are represented among the top ten brokers, state organizations are the most common (rows 1, 3, and 7–10 in Table 3), echoing the pattern detailed in Table 2.

Table 4 lists the G–F brokerage scores based on the organizational subgroup affiliation of the broker. Note that both state and federal organizations occupy coordinator broker roles more frequently than would be expected by chance given the baseline. State organizations also occupy, with significantly high frequency, the role of gatekeeper/representative broker. These findings again demonstrate that state organizations are the most prominent subgroup among the brokers, and thus have the most opportunities for facilitating coordination or transferring valuable resources in this response context.[18]

[17] If information is available about the ordering of the edges, however, one *can* adjudicate between the two types of brokerage. While the network remains undirected, the sequential information introduces a directionality effect since brokerage can only occur forward in time, not backward. That is, once we know which of the edges occurred first among a triad engaged in gatekeeper/representative brokerage, we can distinguish the two brokerage types. We discuss this distinction further when considering the brokerage process in later sections.

[18] These results differ from those of Lind et al. (2008). Whereas local organizations were found to be the primary brokers in previous work, these results indicate that local organizations actually have significantly low frequency of brokerage opportunities in almost all categories. This variation suggests a strong difference in brokerage behavior across relational type and time scale of activity.

### 3.3. Classical insights and limitations

As a measure of static position, a G–F brokerage score summarizes the role of ego as a *potential* bridge while the process of action is left tacit. The G–F measure is ill-suited, however, in contexts where the relational structure changes on a timescale comparable to brokerage activity. The *process* of brokerage is affected by the underlying dynamics of the network structure. Aggregated data require one to implicitly assume that the ordering of edges is irrelevant. Though potentially appropriate in some applications, this assumption could be extremely misleading, especially in contexts for which the ordering or exact timing of relations is crucial for exchange to occur (as in the case of transfer brokerage). As we have discussed, traditional measures of brokerage fail to capture brokerage processes that are intrinsically reliant on the dynamics of the network. The consequences of this limitation manifest in two specific ways. First, the G–F measure may identify brokerage opportunities where none were actually present (false positives), and second, the measure may miss potential brokerage opportunities (false negatives, *e.g.*, the dynamic brokerage example illustrated in Fig. 4).

The empirical findings presented earlier reflect these two limitations of the G–F measure when applied to aggregated, non-dynamic network data. In the current context edges are treated as bidirectional, thus for any realized incomplete two-path brokerage opportunities in either direction are counted. In reality this dual opportunity is not actually present. The temporal nature of the ties restricts transfer to occur in only one direction, but without any information about those dynamics, one cannot know which of the two possible directions was actually realized. In other cases, the G–F measure undercounts brokerage opportunities. Actors who engage in matchmaking brokerage, for example, are completely missed by classical approaches because their brokerage results in the formation of a direct tie between the brokered parties. As a result, while the formation of the direct tie occurred after the parties were brokered, an aggregated view of this interchange would disqualify as an instance of brokerage—a two-path without the third, direct tie. This second limitation impacts the resulting brokerage scores in two ways. First, brokerage scores derived from the G–F measure may be lower as a result of these missed opportunities, but more importantly, the measure also fails to identify nodes who engage solely in matchmaking brokerage. Unfortunately, because errors may occur in either direction (biased upwards or downwards) they are confounded in a way which obscures the results, and there is no way to determine the direction in which the results are biased without a *dynamic* understanding of brokerage.

### 3.4. Dynamic brokerage

Brokerage encompasses a potentially wide range of social behaviors. As discussed previously, the preconditions and subsequent effect on third party ties of the different types of brokerage (transfer, matchmaking, and coordination) are distinct. To accurately measure brokerage opportunities in the dynamic context, one must account for network dynamics. Using the measure of dynamic brokerage formalized in Definition 1, we assess the extent to which the evolving network of collaboration during the Hurricane Katrina response affords actors the opportunity to broker relations between other organizations.

204 organizations (about 13% of the organizations) occupy positions of brokerage in one or more instances over the 13-day period in the Katrina EMON data. The distribution of these organizations by subgroup affiliation, along with the probability of an organization occupying a position of brokerage given its subgroup affiliation, is given in the values specified in parentheses in Table 2. A

**Table 3**
Top ten brokers by total brokerage score using G–F brokerage measure.

| | Organization | Coordinator | Itinerant | Gatekeeper | Representative | Liaison | Total |
|---|---|---|---|---|---|---|---|
| 1 | Colorado Division of Emergency Management (DEM) | 322*** | 240** | 474*** | 474*** | 392** | 1902** |
| 2 | American Red Cross | 20* | 522*** | 168** | 168** | 656*** | 1534** |
| 3 | Texas State Operations Center (SOC) | 980*** | 4* | 125** | 125** | 6* | 1240** |
| 4 | U.S. Federal Emergency Management Agency (FEMA) | 146*** | 112** | 214** | 214** | 146** | 832** |
| 5 | Emergency Management Assistance Compact | 0 | 308** | 24* | 24* | 310** | 666** |
| 6 | Dry Tortugas/Everglades National Park | 70** | 130** | 148** | 148** | 142* | 638** |
| 7 | Georgia State Operations Center | 344*** | 14* | 125** | 125** | 22* | 630** |
| 8 | Florida SERT, Emergency Support Service Branch | 280*** | 20** | 124** | 124** | 22* | 570** |
| 9 | Missouri Emergency Management Agency (EMA) | 130** | 32* | 128** | 128** | 66** | 484** |
| 10 | Alabama EMA, Emergency Operations Center, ESF 9 | 4* | 380*** | 46* | 46* | 0 | 476** |

* Significantly high: $p \leq 0.05$; ** Significantly high: $p \leq 0.01$; *** Significantly high: $p \leq 0.001$.

comparison across these two cases yields insight into the behavior of the two measures in this empirical case.

Under a dynamic formalization of brokerage, 16 new organizations are identified as occupying brokerage roles, compared to those identified by the G–F measure. Each of these organizations occupies a position where bridging opportunities are preceded and/or followed by the presence of a direct tie between the two brokered parties. Seven of these brokers are state organizations, three are federal organizations, four are local organizations, and two are NGOs. Relatively few NGOs fall into this category given their large proportion in the population, though most organizational categories are represented. Each of these 16 organizations occupies a potentially unique social role within the relational context. Matchmaking during the period of disaster response allows the broker to encourage the formation of direct relationships between the brokered parties, which could increase the efficiency of the response or improve resource sharing. This role is distinct because the broker surrenders his role after the process completes. These 16 brokers are missed entirely by the G–F measure. In cases where matchmaking in particular is important to the social context, this could be a severe error.

Table 5 presents the top ten brokers (by total brokerage score) identified by our dynamic brokerage measure. While the organizations represented here are similar to those identified by the G–F measure (given in Table 3), the U.S. Department of Energy's Office of Electricity, Delivery, and Energy Reliability now appears among the top brokers. Perhaps more importantly, however, the top-ranked organization has changed—the Texas SOC now outranks the Colorado DEM in terms of its total brokerage score and has more than *twice* the number of brokerage opportunities than the Colorado DEM. The careful reader will note that under the dynamic measure of brokerage, gatekeeper and representative brokerage scores are no longer indistinguishable, as they were under the G–F measure. This is one of the clear advantages of the brokerage-as-process perspective—the ability to maintain the distinction between gatekeeper and representative roles with undirected network relations. Given the dynamic nature of these network data, it is natural to inquire about an organization's *accumulation* of brokerage potential over time. *Do organizations accumulate brokerage opportunities through repeat encounters with the same sets of partners, or do they broker a different sets of third parties over time?* We are able to study the brokerage process in this manner by adjusting the way in which temporal dependence between brokerage opportunities is defined. Recall the dynamic formalization of the brokerage measure counts the unique opportunities for brokerage defined by the conditions $(bRa)_t$, $(aRc)_{t+i}$, and $(b\bar{R}c)_{\forall t':t<t'<t+i}$. As a result, distinct brokerage opportunities within the same triad that occur over the course of time are counted as *unique*. In other words, it captures repeat opportunities for brokerage within the same triplet of actors. However, one might also consider a form of dynamic brokerage in which repetition *does not* add to an actor's brokerage score. Under this constraint, an opportunity for brokerage within a given triad of actors is viewed as a dichotomous distinction—either a brokerage opportunity does or does not occur over the time scale considered, without regard to the number of unique brokerage opportunities that may have existed. We distinguish between these two approaches by referring to the former as *non-dichotomized* dynamic brokerage (results for which we have already presented) and the latter as *dichotomized* dynamic brokerage. Note that the dichotomized dynamic brokerage measure more closely compares with the G–F measure.

The distinction between the dichotomous and non-dichotomous measures allows one to compare actors who have distinct patterns of brokerage behavior.[19] To better understand this distinction, consider two hypothetical actors. The first brokers relations between numerous different sets of alters. The second brokers relations among a small set of alters, but the opportunities for brokerage are repeated over time. The first actor continually engages in new brokering roles, brokering new pairs of alters each time. The second actor, however, might learn about alters through previous relationships, and as time progresses, this may decrease the time and energy needed to broker the pair. The potential drain on the brokering actor's resources and time is very different for these two cases. In the context of information exchange, for instance, the first actor has only one chance to pass information between the alters, whereas the second actor has multiple occasions on which to facilitate the exchange. The capacity to distinguish these two types of brokerage accumulation is a distinct contribution of our dynamic extension.

Table 6 lists the top ten brokers, ranked by total brokerage score, obtained by the *dichotomized* dynamic brokerage measure. These ten organizations are identical to those identified in Table 3, the

**Table 4**
Brokerage by organizational subgroup using G–F brokerage measures.

| Subgroup | Coordinator | Itinerant | Gate/Rep | Liaison | Total |
|---|---|---|---|---|---|
| Federal | 372** | 490 | 384 | 478 | 2108 |
| State | 3032*** | 1184 | 1752* | 808 | 8528** |
| Local | 16 | 22... | 8... | 20... | 74... |
| NGO | 452 | 648 | 267 | 714 | 2348 |
| International | 0 | 6 | 0 | 30 | 36 |
| Unknown | 2 | 64 | 11 | 22 | 110 |

* Significantly high: $p \leq 0.05$; ** Significantly high: $p \leq 0.01$; *** Significantly high: $p \leq 0.001$; . Significantly low: $p \leq 0.05$; .. Significantly low: $p \leq 0.01$; ... Significantly low: $p \leq 0.001$.

[19] The distinction between repeated *versus* new relationships has important consequences in the case of inter-organizational collaboration, as well as other social settings. Inter-organizational collaboration can often be hindered by conflicting organizational practices and procedures. With repeated interaction, the cost of such barriers would likely be decreased, affording more efficient transactions over time. This might suggest interesting consequences for cases of transfer brokerage in which the process of transfer becomes more efficient with time.

**Table 5**
Top ten brokers identified by the *non-dichotomized* dynamic brokerage measure.

| | Organization | Coordinator | Itinerant | Gatekeeper | Representative | Liaison | Total |
|---|---|---|---|---|---|---|---|
| 1 | Texas State Operations Center (SOC) | 2100*** | 279** | 1491*** | 1470*** | 636** | 5976** |
| 2 | Colorado Division of Emergency Management (DEM) | 496*** | 315** | 713*** | 776*** | 702** | 3002*** |
| 3 | American Red Cross | 99** | 604** | 276** | 321** | 338** | 1638** |
| 4 | Georgia State Operations Center | 523*** | 90** | 422** | 366** | 170* | 1571** |
| 5 | Alabama EMA, Emergency Operations Center, ESF 9 | 65** | 315** | 265** | 268** | 506** | 1419** |
| 6 | U.S. Department of Energy, Office of Electricity, Delivery and Energy Reliability | 3* | 176** | 36** | 35** | 424** | 674** |
| 7 | Missouri Emergency Management Agency (EMA) | 225** | 44* | 145** | 189** | 65* | 668** |
| 8 | U.S. Federal Emergency Management Agency (FEMA) | 17** | 151** | 87** | 99** | 290** | 644** |
| 9 | Dry Tortugas/Everglades National Park | 92** | 53** | 139** | 146** | 132** | 562** |
| 10 | Emergency Management Assistance Compact | 8* | 230** | 74** | 46** | 155** | 513** |

* Significantly high: $p \leq 0.05$; ** Significantly high: $p \leq 0.01$; *** Significantly high: $p \leq 0.001$.

**Table 6**
Top ten brokers identified by the *dichotomized* dynamic brokerage measure.

| | Organization | Coordinator | Itinerant | Gatekeeper | Representative | Liaison | Total |
|---|---|---|---|---|---|---|---|
| 1 | Colorado Division of Emergency Management (DEM) | 298*** | 193** | 404*** | 467*** | 406** | 1768*** |
| 2 | American Red Cross | 99** | 357*** | 241*** | 287*** | 244** | 1228*** |
| 3 | Texas State Operations Center (SOC) | 420*** | 59** | 315*** | 294** | 138** | 1226** |
| 4 | Georgia State Operations Center | 149** | 50* | 174** | 119** | 86* | 578** |
| 5 | Dry Tortugas/Everglades National Park | 92** | 53** | 137** | 145*** | 132** | 559*** |
| 6 | U.S. Federal Emergency Management Agency (FEMA) | 17** | 121** | 82** | 93** | 244** | 557** |
| 7 | Alabama EMA, Emergency Operations Center, ESF 9 | 35** | 85** | 104** | 107** | 148** | 479** |
| 8 | Emergency Management Assistance Compact | 8* | 199** | 71** | 43** | 150** | 471** |
| 9 | Missouri Emergency Management Agency (EMA) | 123*** | 32* | 86** | 130** | 51* | 422** |
| 10 | Florida SERT, Emergency Support Service Branch | 153** | 27* | 78** | 109** | 31* | 398** |

* Significantly high: $p \leq 0.05$; ** Significantly high: $p \leq 0.01$; *** Significantly high: $p \leq 0.001$.

results after using the original G–F measure, but we observe slight differences in the ranks (the last three organizations have shifted in position). As with the G–F measure, the Colorado DEM is the top-ranked organization by total brokerage. Many of the brokerage scores computed with the dichotomized measure are actually *lower* than those computed from the G–F measure. This decrease results from the restriction to valid *time-ordered* relational configurations. The new results eliminate falsely identified brokerage opportunities.

Brokerage scores classified by organizational subgroup affiliation are given in Table 7. In both cases, brokerage opportunities for federal organizations are no greater than might be expected by chance given the baseline model. This stands in contrast to the findings obtained from the G–F measure (as given by Table 4), in which federal organizations were shown to occupy positions of coordinator brokerage with significantly high frequency. State organizations are the *only* organizational subgroup to occupy positions of brokerage with a frequency significantly higher than expected by chance. Local organizations are significantly *less likely* to occupy most positions of brokerage.

### 3.4.1. *Brokerage process consistent patterns*

The brokerage processes discussed previously, those outline in Fig. 1, imply specific temporal sequences of relations. Matchmaking brokerage, for example, implies a time-ordered two-path followed by the formation of an alter-alter tie. Transfer, matchmaking, and coordination each have associated tie sequences that are consistent with their respective underlying processes. Therefore, one can use the observed network dynamics to classify the extent to which brokerage opportunities are consistent with the three brokerage classes. These *brokerage consistent patterns* (BCPs) allow for a straightforward comparison between organizational attributes and brokerage mechanisms not possible in classic approaches to brokerage.

Brokerage consistent patterns are defined as follows: a transfer brokerage relation is characterized by a time-ordered two-path connecting two alters who previously could not reach each other via a direct tie; a matchmaking condition is characterized by a time-ordered two-path followed by a third party tie; a coordination condition is characterized by sequence where a third party tie may precede the brokerage opportunity but cannot follow it (as the brokerage relation in this case obviates the need for a direct connection). We consider the upper bound on these BCPs as seen in Table 8 based on a non-dichotomized dynamic measure of brokerage. Again, permutation null models are used to perform significance testing.[20]

Considering the BCPs in relation to organizational attributes provides an interesting contrast to previous results. With respect to coordination brokers, local organizations were the only type to occupy this role with significantly high frequency. In each of the previous analyses, local organizations did *not* play a prominent role, and would likely have been ignored as potential important brokers. NGOs and local organizations have lower than expected opportunities consistent with transfer brokerage. NGOs, however, have the highest number of matchmaking consistent roles (though not significantly high). This more subtle accounting of brokerage reveals that local organizations play a specific role within the observed collaboration networks: they act primarily to permit a lack of tie between other organizations, rather than serving as conduits for information and resources, or bringing together organization through matchmaking. This latter function, by contrast, is carried out by the state and federal organizations, whose role in the dynamic network appears to be primarily to bridge third parties lacking instances of direct collaborative contact. Although arguably consistent with the National Response Plan governing activities in response to events of national significance at the time of the Katrina disaster (Of, 2004), the tendency of state and federal organizations to stand between other organizations—as opposed to encouraging

[20] This measure is an upper bound because it represents opportunities consistent with each pattern rather than exact occurrences. However in a given context additional information about each relation (*e.g.*, a measure of information exchanged) might make classification more exact.

**Table 7**
Brokerage by organizational subgroups. Values obtained from our non-dichotomized dynamic brokerage measure are given in non-shaded cells, and those obtained from our dichotomized dynamic brokerage measure are given in shaded cells.

| Subgroup | Coordinator | | Itinerant | | Gatekeeper | | Representative | | Liaison | | Total | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Federal | 46 | 46 | 643 | 450 | 251 | 238 | 212 | 201 | 932 | 613 | 2084 | 1548 |
| State | 4428*** | 1817*** | 1583 | 869 | 3903*** | 1797*** | 4013*** | 1910*** | 2766 | 1379 | 16693*** | 7772*** |
| Local | 5... | 5... | 33... | 29 | 13... | 13... | 14... | 14... | 21... | 19... | 86... | 80... |
| NGO | 286 | 240 | 768 | 488 | 428 | 366 | 493 | 431 | 434 | 331 | 2409 | 1856 |
| International | 2 | 2 | 19 | 9 | 7 | 7 | 6 | 6 | 12 | 12 | 46 | 36 |
| Unknown | 2 | 2 | 61 | 55 | 14 | 14 | 19 | 19 | 7 | 7 | 103 | 97 |

* Significantly high: $p \leq 0.05$; ** Significantly high: $p \leq 0.01$; *** Significantly high: $p \leq 0.001$; . Significantly low: $p \leq 0.05$; .. Significantly low: $p \leq 0.01$; ... Significantly low: $p \leq 0.001$.

**Table 8**
Patterns of brokerage potential.

| Organizational subgroup | Brokerage consistent pattern | | |
|---|---|---|---|
| | Transfer | Matchmaking | Coordination |
| Federal | 2066*** | 18 | 3... |
| State | 16,596*** | 97 | 31 |
| Local | 30... | 56 | 29* |
| NGO | 2255... | 154 | 30 |
| International | 38*** | 8 | 0 |
| Unknown | 102*** | 1 | 0 |

* Significantly high: $p \leq 0.05$; ** Significantly high: $p \leq 0.01$; *** Significantly high: $p \leq 0.001$; . Significantly low: $p \leq 0.05$; .. Significantly low: $p \leq 0.01$; ... Significantly low: $p \leq 0.001$.

third-party collaboration—may have contributed to the difficulty of the post-landfall response.

Coordination brokerage is arguably important in a disaster response like that to Hurricane Katrina because it allows for efficient negotiation in situations where tie maintenance is expensive. Within disaster contexts, coordination among the actors, despite disrupted communication channels and infrastructure, requires the emergence of brokerage roles. Direct communication and coordination between organizations may be difficult, if not impossible; brokers facilitate the flow of information and physical goods (Marsden and Lin, 1982). However, not all organizations have the capacity and infrastructure to maintain large numbers of collaboration relationships. Roles which allow coordination without the formation of costly collaboration ties are extremely important. Despite *a priori* hypotheses that large federal organizations are the ones capable of occupying these roles (they have established infrastructure and resource access), we find that local organizations play this role, at least in the early response to Katrina. This has practical implications for response planning for disasters of this type.

### 3.5. Implications of the brokerage-as-process approach

Using the case of brokerage role occupancy in emergent networks of collaboration during disaster response, this work presents a comparison between a traditional measure of brokerage and the dynamic extensions of that measure that we have developed. Differences between the brokerage opportunities identified in each framework have important consequences for subsequent conclusions about brokerage behavior. While the classic measure of brokerage, formalized by Gould and Fernandez (1989), captures a large portion of the brokerage opportunities in the Katrina EMON, it fails in predictable ways. These failures are the direct result of its inability to handle network dynamics, and are attributable to three specific shortcomings of the traditional approach. First, static measures of brokerage (like the G–F measure) do not account for opportunities that span multiple time points. Second, they do not account for processes that involve matchmaking brokerage. Finally, these measures cannot distinguish between repeated and unique structural arrangements over time. It is because of these three important limitations of the traditional approach that we developed our dynamic measure of brokerage. Accounting for the underlying dynamic nature of relational ties in a network allows for a more thorough investigation of the brokerage opportunities afforded to the actors involved and eliminates both the false positive and false negative errors to which the G–F measure is prone, as we have demonstrated here in the case of an inter-organizational collaboration network in the context of a disaster. The process perspective allows for a more nuanced view of brokerage, wherein distinctions can be made between two patterns of brokerage. The first pattern characterizes organizations that occupy many different positions of brokerage among a diverse set alters, whereas the second pattern characterizes those organizations that accumulate brokerage roles through repeated opportunities with a potentially smaller set of alters. This feature of dynamic brokerage is very powerful and these two behavioral patterns have different social implications.

These Katrina data also illustrate an interesting consequence of accounting for network dynamics in networks of undirected relations, as the *temporal* ordering of edges imposes a directionality on brokerage structures. Trivially, one can now distinguish between gatekeeper and representative brokerage roles in networks of undirected relations where it was previously not possible under the traditional approach. In this work we also develop the notion of a *brokerage consistent pattern*, which allows for a classification of brokerage opportunities according to consistency with the three brokerage mechanisms outlined at the outset. This additional level of detail, which is not discernible in the traditional treatment of brokerage, adds a more nuanced view of brokerage in the context of dynamic networks. In the case of the Katrina EMON, exploring BCPs significantly alters the conclusions drawn about important organizations for brokerage behavior. Local organizations are the only subgroup to exhibit significantly high instances of coordination-consistent brokerage sequences of behavior. Coordination processes are vital to disaster response because they allow for efficient information transfer, exchange of manpower, etc. without the formation of potentially costly ties. This dimension of brokerage would have been missed altogether by traditional approaches.

## 4. Discussion

Studies of bridging behavior have a strong tradition within network research. We add to this literature by re-formulating structural concepts of brokerage to bring them more in line with their original dynamic motivation. Formalizing a measure of dynamic brokerage allows for a more nuanced characterization of relational sequences that constitute bridging opportunities in a dynamic relational structure. Using the illustrative case of an emergent collaboration network during the Hurricane Katrina response, we demonstrate the important differences that result between use of the classic measure of brokerage developed by Gould and Fernandez (1989) and the dynamic extensions that we have developed here. In general, by incorporating structural dynamics into measures of brokerage, we are able to identify additional opportunities for brokerage that the traditional measure cannot detect. In addition, our dynamic extension of the brokerage measure eliminates the problem of falsely identifying brokers, a clear pitfall associated with the traditional measure developed by Gould and Fernandez.

Throughout this work we have motivated the development of a dynamic measure of brokerage by considering three categories of brokerage mechanisms—transfer, matchmaking, and coordination—and have emphasized extensions to the original approach by Gould and Fernandez which preserve as much as possible the fundamental intuitions behind the concept of brokerage. Indeed, Gould and Fernandez have not only motivated the temporal approach illustrated here, but also forced attention to the relationship between brokerage structures and network dynamics. One of the interesting consequences of their original work is the notion that brokerage structures might be intrinsically related to structural dynamics, and this is something we view as crucial to understand in order to more fully account for and measure brokerage. As in the cases of matchmaking and coordination brokerage, for instance, what begin as similar structural configurations can ultimately have very different influences on the subsequent existence of the third party tie. In the former case, the brokerage relation *increases* the change of observing the third edge while the latter *decreases* the chance of observing the third edge. In other words, the measure could potential aid in causal inference on the relationship between potential brokerage acts and structural dynamics. Moreover, it might offer insight into the much debated association between brokerage positions and benefits accrued in such positions Burt (1992), Buskens and van de Rijt (2008). We are encouraged by our dynamic extension of the brokerage measure and its ability to distinguish these mechanisms, and we also recognize the need for further development to more fully understand the connections between network dynamics and the implications of the mechanisms.

We recognize that the notion of matchmaking is closely tied to the concept of triadic closure, which itself has been an important theoretical concept both in network analysis and sociology more generally (Simmel, 1949; Heider, 1946; Granovetter, 1973). Triadic closure is the tendency for individuals $b$ and $c$ to be linked if $b$ is tied to $a$ and $a$ is tied to $c$. This phenomenon arises in many common social situations, such as in the case of friendships. A broker may serve as a mediator with the goal of bringing together as friends, for instance, previously disconnected alters. It is precisely this role, *tertius iungens* (or "third who joins"), that Obstfeld (2005) argues for in his work on organizational innovation. Unfortunately, this concept has not received its due attention within the literature, perhaps because existing approaches to brokerage have been ill-equipped to handle such cases until now. While traditional measures of brokerage cannot identify matchmaking as a *brokered* activity, our dynamic approach does. This feature of our dynamic measure will likely be important in contexts in which this behavior is expected or likely to occur, as in networks of collaboration.

While the emphasis on our development of a dynamic extension to the measurement of brokerage has been on *parsimonious* extension of the G–F measure, we recognize that our approach is not the only means of conceptualizing brokerage within a dynamic framework. For example, one might consider a measure such that the score assigned to a particular brokerage opportunity is proportional to the length of time between the appearance of the two edges of the two-path. In other words, the length of time between the appearance of some initial edge between a third-party and the broker and the subsequent appearance of an edge from the broker to some other party may have important implications for the feasibility of the exchange. If relations serve as conduits for the passing of time-sensitive information or goods, brokerage potential may thus decay as the length of the window between the two edge events increases. While this line of thinking suggests potentially fruitful avenues for future work, we restrict ourselves here to preserve the core ideas of brokerage as elaborated by Gould and Fernandez (1989) and to extend those ideas to the dynamic context in as natural a way as possible.

This research contributes to the field of social network research by extending the tools available to network researchers; it also contributes to sociology more generally by elaborating on the roles and processes associated with bridging and brokering. We introduce a simple measure of dynamic brokerage and discuss two formulations of this measure to allow for distinction in dynamic brokerage behavior. Our effort to formalize a measure of dynamic brokerage brings traditional network concepts into a dynamic framework, allowing for new explorations and application.

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