Workplace Networks and the Dynamics of Worker Organizing

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Abstract

What role do workplace social networks play in successful labor organizing? We present establishment-level evidence of the importance of organizer attention to workplace networks. We process over 80,000 unstructured organizer field notes from almost 120 store-level campaigns conducted at Walmart stores from 2010 to 2015 to reconstruct workplace networks as perceived by the organizer. We match these to an organizing outcome – signing a card indicating membership in a worker organization. We create a measure of network-driven organizing: the rank correlation between organizer attention to a worker and that worker's network centrality, illustrated with two case studies based on interviews with 35 workers and a qualitative analysis of organizer notes. The measure is positively and robustly correlated with campaign success; going from 0 to 1 increases cards signed by 70-80%, over a baseline mean of 23 cards. We leverage the decentralized team structure of the organizing to establish causality by using a leave-one-out team average of store-level network-driven organizing as an instrument. In the tradition of problem-solving sociology, the proposed measure might be adopted by labor organizations to assess organizing strategies.

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1 Introduction

Labor unions and other worker voice organizations have recently received renewed public, policy, and academic attention. In the U.S., these organizations have generally formed through a process of organizing at the level of the establishment, as staff organizers and worker leaders persuade other workers within a particular workplace to engage in collective action in order to establish a union or otherwise improve working conditions. In this paper, we use new data on 120 labor organizing campaigns at the same employer, Walmart, to examine the effect of network-driven organizing strategy on labor organizing success.

While the effects of unions on key outcomes like inequality and racial disparities are the subject of extensive literatures, there is little quantitative research on the dynamics of organizing new unions or worker organizations. Owing to both employer opposition and labor law, recognition of a new union or other worker voice organization entails overcoming formidable barriers to worker collective action. Almost 50% of non-union private-sector workers say they would vote for a union if asked, but private union density remains at just over 6%, suggesting there is unrealized latent demand for unions (Hertel-Fernandez et al., 2022). Workplace social capital and social networks among workers may be key to overcoming such barriers (Naidu, 2022; Shepherd, 2021). But the detailed examination of the role of relationships in the labor-organizing process has remained largely confined to qualitative case studies. Quantitative data on worker collective action and networks during an organizing drive remains rare, and our paper helps fill this gap.

In contrast to the literature on unions, the social movement literature has long recognized the role of organizing and social networks to collective action outcomes. This interdisciplinary literature supports the idea that social networks are important to explaining movement participation and nonparticipation (for a succinct review, see Krinsky and Crossley (2014)). Recent literature in economics has developed theoretical models and causal empirical evidence showing that network structure is important for participation in political collective action in diverse contexts (Jackson, 2010; González, 2020; Naidu et al., 2021; Cantoni et al., 2019), but this literature has not examined the labor organizing context, despite its importance for core labor economics questions such as the union premium and selection into union membership (Farber et al., 2021; Freeman and Medoff, 1984). Survey experiments suggest that workplace collective action exhibits strategic complementarities (Naidu, 2022; Hertel-Fernandez et al., 2020), so that organizer investments in incentivizing agents with high network centrality should improve collective welfare (Galeotti et al., 2021).

In sociology, scholars have offered a range of explanations for why social networks may be important to organizing, from processes of interpersonal influence, whereby people mobilize (or demobilize) their neighbors (Kim and Bearman, 1997; McAdam and Paulsen, 1993; Polletta, 2014); to processes of information diffusion, whereby networks allow people to understand others' intentions for participation and thus to overcome collective action problems (Chwe, 1999; Granovetter, 1978; Kim and Bearman, 1997; Macy, 1991; Oliver et al., 1985); to processes of collective identity formation (Gould, 1993, 1995; Tilly, 1979), whereby networks change how people understand themselves, and thus the collectivities on behalf of which they are willing to act.

For all its promise, however, this existing literature has empirical and theoretical limitations. Empirically, the vast majority of scholars who have explored the relationship between the formal structure of social networks and movement participation rely on simulation models rather than empirical evidence (Kim and Bearman, 1997; Oliver et al., 1985; Chwe, 1999; Macy, 1991; Gould, 1993); for an exception see Gould (1995)). This is likely a result both of the difficulty of obtaining relational data regarding participants and non-participants within the context of a social movement, and of the small number of cases of insurgency within most social movement analyses, which make it difficult to generalize about the importance of network characteristics beyond the context of a particular campaign.

Theoretically, the literature is limited by the assumption that networks (and network positions) are stable characteristics of a setting that exist outside the control of movement actors themselves. Scholars have thus tended to overlook the ways in which movement actors might attend and respond to—-as well as intervene upon—-network structures and processes. Such a second-order understanding of, and strategic engagement with, social networks is likely a key characteristic of one of the most important yet undertheorized roles within a social movement or labor organizing campaign: that of the "organizer." Understanding whether and how organizers' mapping of, and engagement with, the networks of potential supporters impacts the success of a campaign has implications both for our academic understanding of the role of networks in movements, as well as for movement organizations themselves.

Below, we present new statistical evidence on the determinants of success in labor organizing at America's largest employer, Walmart. Motivated by the qualitative literature on labor organizing as well as simple models of social learning, we develop a new measure of network-driven organizing: the correlation between an organizer's attention to a potential participant and that potential participant's centrality in a wider network of potential participants, as this network is understood by the organizer. We then test this measure using over 80,000 detailed organizing field notes collected by labor organizers from 120 store-level organizing drives at Walmart between 2010 and 2015. Our main outcome of interest is the number of membership cards signed within a store, a measure of collective action. Drawing on interviews with Walmart workers involved in the campaigns, in combination with a qualitative examination of the organizer notes, we illustrate how successful and unsuccessful organizer strategies differentially attend to workplace networks. Quantitatively, we show that when organizers target their effort and attention to the workers they perceived to be central in the workplace relationship network (i.e., use network-driven organizing), there are significantly higher levels of collective action, as measured by membership cards signed.

We further probe causality by constructing an instrumental variable based on the organizing team assigned to a given store. The worker organization we study divided Walmart stores into different regions, and each region received a different team of organizers, with different organizing strategies and cultures. We construct a leave-one-out average of network-driven organizing of the team assigned to a given store, and show that this variable is both strongly correlated with the level of network-driven organizing as well as with the number of cards signed. Under the assumption that the team assignment is independent (or independent conditional on observable variables) of other determinants of collective action at the store level, instrumental variable estimates show a large effect of network-driven organizing on cards signed.

The estimated coefficient magnitudes are large and meaningful in our context: going from a 0 correlation between network centrality and organizer effort to a perfect correlation of 1 results in between 70 and 80% increase in cards signed, with instrumental variable estimates increasing to 140%. Given the low baseline rate of card-signing, with only 13 cards signed at the median store and 23 cards on average, network-driven organizing is not on its own a magic bullet to sway an organizing drive. Nevertheless, it may be decisive in cases where a sizeable minority of workers are initially interested in organizing. We discuss the magnitudes and their interpretation in section 6.3

2 Organizers as Networkers

The specific strategies organizers use have been understudied in quantitative work. While social scientists generally appreciate the importance of organizers in explaining the emergence and success of social movements, they have struggled to define precisely what it is that these leaders do and how they do it. This is related to a more general struggle within the social sciences to theorize the practices by which actors successfully change institutional environments. While a wide variety of interesting theoretical constructs—from "institutional entrepreneurship" (DiMaggio, 1988) to "robust action" (Padgett and Ansell, 1993) to "social skill" (Fligstein and McAdam, 2012)—have been proposed, such constructs tend to be defined in terms of the outcomes they produce (e.g. "Social skill can be defined as the ability to induce cooperation by appealing to and helping to create shared meanings and collective identities," (Fligstein and McAdam, 2012, pp. 46), which limits their usefulness in terms of explaining when such collective outcomes succeed and when they fail.

Within the context of social movements, early efforts at theorizing the "organizer" recognized the importance of an organizer's use of social networks. In her account of the origins of the women's movement, for instance, Jo Freeman (1973) discussed the existence of "communication networks" as a necessary but insufficient condition for movement emergence. While occasionally a crisis could "galvanize[] the network into spontaneous action" (Freeman, 1973, pp. 794), she observed, rarely could a movement emerge or persist without the strategic action of organizers. However, while recognizing that the "role of the organizer in movement formation is… [a] neglected aspect of the theoretical literature" (Freeman, 1973, pp.807), Freeman did not go much further in specifying either the network or the work that organizers do in relationship to it.

The most explicit treatment of organizing may be Charles Payne's (Payne (2007)) *I've Got the Light of Freedom: The Organizing Tradition and the Mississippi Freedom Struggle*, in which he describes the work of the Mississippi Student Non-Violent Coordinating Committee field staff in 1963: a group of forty-one workers who were mostly young, "mostly Black, mostly southern, [and] mostly from working-class backgrounds" (Payne (2007): 237). Payne describes in exacting detail the many ways that these young organizers went about the "slow work, respectful work" (Payne (2007): 243) of organizing. In his account, the organizer played many different roles at once: "Organizers had to be morale boosters, teachers, welfare agents, transportation coordinators, canvassers, public speakers, negotiators, lawyers, all while communicating with people ranging from illiterate sharecroppers to well-off professionals and while enduring harassment from the agents of the law and listening with one ear for the threats of violence" (Payne (2007): 246). Tying together these multiple roles was the goal of identifying, recruiting, and developing potential movement leaders and supporters. On the one hand, the organizer worked to identify and develop "informal leaders" (Payne (2007): 248-249) in a community, those people who were not necessarily endowed with any institutional authority but who were well liked and well respected by others; on the other hand, the organizer reached out to everyone they could contact through canvassing, "going door-to-door, trying to draw people in" (Payne (2007): 250). Payne summarizes the role of an organizer by quoting the Civil Rights leader Bob Moses, who responded to a question about how to organize a town by saying,

> "By bouncing a ball," he answered quietly.
>
> "What?"
>
> "You stand on a street and bounce a ball. Soon all the children come around. You keep on bouncing the ball. Before long, it runs under someone's porch and then you meet the adults" (Payne (2007): 243).

The organizer in Payne's account works within existing ties and developing new ones, with the goal of recruiting new people to a movement and deepening the commitment of those already involved.

Building on such historical case studies, sociologists and political scientists have sought to distinguish "organizing" from other types of movement activity. In unpublished course notes, which have nevertheless diffused widely among movement actors and academics alike, Marshall Ganz (2006) provides a succinct definition of organizers as those who "identify, recruit, and develop leadership; build community around leadership; and build power out of community."

Jane McAlevey (2016), focusing on the labor movement in particular, discusses how successful organizers "analyze the workers' preexisting social groups" (McAlevey, 2016, pp. 34) using conversations with workers to learn which of their peers are considered "organic leaders" in their workplaces. For McAlevey, leaders are not determined based on prior involvement in or enthusiasm toward the union but rather based on the influence they have with their coworkers. McAlevey quotes a labor organizer, Kristin Warner, who says, "[Organic leaders are] almost never the workers who most want to talk with us... They have a sense of their value and won't easily step forward, not unless and until there's a credible reason" (McAlevey, 2016, pp. 34).

Likewise, Hahrie Han (2014, pp.14), in her study of a range of NGOs, suggests that organizers "do not simply aggregate individuals but also create new relationships between them that generate new commitments and resources." In particular, Han continues, organizers do things like "make requests for action that bring people into contact with each other... " (Han, 2014, pp. 16); "focus on building relationships and community through interdependent (as opposed to individual) action" (Han, 2014, pp. 16); and develop people's leadership through "extensive training, coaching, and reflection" (Han, 2014, pp.17).

While this nascent literature on organizing uses the metaphor of networks to describe the work that organizers do, organizing has not previously been defined or evaluated in formal network terms. By bridging this literature on organizing with previous work that has examined social movements using more formal network methods, we can operationalize the concept of "network-driven organizing" and look at whether it is indeed associated with success at generating collective action.

3 Data

We use several types of information from a voluntary association of employees working at Walmart – OUR Walmart (henceforth, "OUR"). We make use of an anonymized database maintained by OUR that includes information about the workers with whom paid organizers for OUR were in contact between 2010 and 2015. During this period, the paid organizers (some of whom were former Walmart workers themselves) sought to engender support from employees for actions and to recruit employees to be members of OUR. (The organization no longer has a similar membership structure.) The organizers would do so by making initial contact with workers in a store through brief and often surreptitious interactions in the workplace. During the period in which these data were collected, OUR and its members advocated for Walmart workers through attendance at the company's annual shareholders' meeting, media stories about work conditions, and smaller-scale campaigns at specific stores. It did not seek union recognition.

3.1 OUR Walmart Member Information and Card Signing

The database includes information about all members of OUR and the stores for which they work or worked. The database also includes the date on which a worker was entered into OUR's database and, for those employees who became OUR members, the date on which the member signed an OUR membership card. We use card signing as a meaningful outcome indicating successful organizing, as it was associated with a commitment to pay $5 in monthly dues. The organizer's objective was to gain signed cards, with the idea that the larger the share of workers who had signed cards, the more successful a variety of collective actions would be, ranging from specific store-level changes to policy, to specific national-level policy demands like "Respect the Bump" (pregnancy benefits), to actions like Black Friday strikes, in which workers walked off the job on the busiest shopping day of the year.

We use the number of signed membership cards as our primary indicator of store-level collective action, and we aggregate the total number of signed cards to the store level (logged). As this measure is dependent on a variety of campaign-level characteristics beyond our network-driven organizing measure, we take care to either normalize by or control for mechanical determinants of card signing such as the length of the campaign. Campaign length, measured as the number of weeks between the first and last organizer notes linked to the store, ranges from 63 weeks to 251 weeks.

3.2 OUR Walmart Field Organizer Notes

In addition to member information, the database includes a total of 81,020 "Notes" written by organizers in accordance with procedures established by OUR. Each note was logged by an organizer after they had a conversation with a worker, along with the date of the conversation and the unique identifier of the worker. We use these notes for two main purposes: first, we measure organizer attention to a worker as the number of notes indicating a conversation with that worker; second, we identify other workers' names in the text of these notes as indicators of relationships between workers that have been discovered or cultivated by the organizers (see subsection 3.3).

Organizing activity, as reflected through card-signing and organizer notes, varies dramatically from store to store, and we show time-series graphs of this activity in a random set of stores in Figure 1. We show the distribution of cards signed across stores (as well as the log) in Figure 2, and we provide some examples of the raw note data in Appendix B. [FIGURES 1 AND 2 HERE]

3.3 Defining and Coding Network Edges

We construct the organizer's conception of the store-level network based on the occurrence of other store employees' names within organizer notes about a worker. Based on the notes associated with each worker, we consider the worker to have a relationship with a second worker (denoted by a 1 in the store-level adjacency matrix) if the second worker's name "matches" a name mentioned in the text of the note. A "match" is defined by a worker in the same store's first name appearing in the text. If more than one worker shares the first name, coders attempted to disambiguate the matches using the next word in the note's text. We determine whether this next word is the last name or the initial of either match by checking if either match's last name starts with the next word.

This method of network construction reflects an organizer's attention to relationships between employees within a store. Relationships that organizers recorded among employees could take two forms: those that pre-existed the organizer's attention and efforts (e.g., friendship or family relationships that the organizer recorded), and those that the organizer facilitated among employees (e.g., asking two employees to come to a meeting together). We combine both of these types of relationships into an adjacency matrix representing any type of relationship between employees. We emphasize that the network does not represent the "true" underlying relationships between employees, but instead represents the way the organizer conceives of the set of relationships among employees. Within each store adjacency matrix, we calculate the centrality of each individual using two centrality measures: degree centrality and eigenvector centrality. The centrality measure of an employee reflects the number of coworkers that the organizers perceived to be socially connected to that employee through any type of relationship (degree centrality) or the calculation of the relative influence of an individual employee based on the eigenvector score of his or her network connections (eigenvector centrality).

3.4 Network-Driven Organizing

Our key independent variable is our measure of network-driven organizing. The measure is based on field organizers a) recording relationships among employees in a store and b) recording that they spent more organizing time (assessed by the number of times an an organizer had a conversation with an employee) with those central employees, which we refer to below as organizer attention. In order to ensure that these two factors vary independently of each other, our measure is calculated as the number of organizer notes for any individual employee minus notes that record the relationships used to measure their centrality.

Given a network adjacency matrix in store j A^j, we define the network-driven organizing measure as the within-store rank-correlation between centrality (either degree or Eigenvector centrality) and organizer effort (number of notes that do not contain information about relationships with other employees, i.e., non-edge notes):

$$NDO_j = Corr(Rank(Cent_i^j), Rank(Notes_i^j))$$

Where $Cent_i^j$ is the degree or Eigenvector centrality of employee i at store j, $Notes_i^j$ is the number of non-edge organizer notes mentioning employee i, and $Corr()$ is the within-store correlation between employee centrality and the number of non-edge notes that include that employee taken over the $I(j)$ workers in the dataset for the duration of the campaign at store j. The main measure is the within-store (and, necessarily, within-campaign) correlation between organizer attention $Notes$ and employee centrality $Cent$. This measure can also be interpreted as the cosine distance between normalized organizer effort and normalized centrality, which Galeotti et al. (2021) show characterizes the optimal intervention in network games with strategic complements.

We use rank correlations between organizer effort and worker centrality in our main specifications in order to minimize the influence of outliers and any non-normality in the underlying distributions. The distributions of the network-driven organizing measures are shown in Figure 3, and both versions have means slightly below 0, and vary from -0.5 to 0.56. We show results using Pearson correlations in the Appendix. [FIGURE 3 HERE]

We illustrate the data underlying this measure in Figure 4, which shows the networks corresponding to the Pico Rivera (one of the highest levels of network-driven organizing) and Federal Way (one of the lowest) stores, with the size of the nodes (employees) scaled by the amount of organizer attention they received. Quantitatively, the network-driven organizing level of Pico Rivera is .56 while is it close to 0 at Federal Way. [FIGURE 4 HERE]

Summary information for the data is provided in Table 1. [TABLE 1 HERE]

3.5 Organizer Teams

Each paid organizer belonged to one of twelve teams, which were formed based on the geographic region within which they were organizing (Southern California, Dallas, Chicago, Central Florida, etc.) Each team was supervised by a lead organizer who was responsible for directing the work of the organizers, and provided informal and formal organizing trainings for the rest of the organizing staff. Since OUR's goals were somewhat indeterminate, in that organizers were not trying to form unions, teams had quite a lot of scope for experimentation, meaning that the team cultures and approaches varied substantially. Central Florida's team, for example, was led by a former Walmart associate without prior union organizing experience. She developed an innovative online-to-offline approach to organizing in which the team would identify potential supporters through online group conversations before meeting them in person. In contrast, the Southern California team was led by someone with years of experience as a union organizer, and so brought a more traditional union organizing approach to her team's work. In Chicago, the mostly-Black organizers discussed their work as being a modern-day Civil Rights movement, while in Dallas, organizers with religious experience discussed it as a David versus Goliath struggle. As we will see below, these teams' different approaches were differently associated with the network-driven organizing approach we test in this paper.

4 Qualitative Evidence From Two Walmart Campaigns

Before turning to our quantitative results, we use two case studies, one of a successful campaign that yielded many signed cards and one of a campaign that did not, to help illustrate what network-driven organizing looks like in practice.

Any store will have an existing, heterogeneous set of relationships among employees. Some of these relationships will be kin or friendship relationships, and others will be relationships based on shared experiences, as when workers share a shift or have children who attend the same school. The network we observe in these stores is one where the organizer is both learning about these existing ties and creating organizing-relevant ties by inviting coworkers to attend meetings together, suggesting that they talk with each other, and meeting with them together. To the extent that organizers continue to follow up with people who have more contacts, they are pursuing a network-driven strategy such that high centrality people receive more energy and effort.

4.1 Organizing with the Network

The organizing campaign at a store in Pico Rivera, a town in southeast Los Angeles County, began like it did in many other stores, with organizers from OUR Walmart trying to speak to as many workers as they could. This could be a somewhat long and painful process. For example, the very first worker that organizers recorded in their notes, in November of 2010, was Juan. While he thought that organizing with OUR Walmart was a "good idea," he told the organizers, Juan wanted to wait until after the holidays to "see what happens." Organizers contacted Juan again in December, when he said he did not "want to be the first person in the store" to sign up; in mid-January, when he was "still undecided"; and again in March of 2011, when an organizer visited him at his home and spent at least ninety minutes in conversation, at which point he said he "still wants to wait and see if his situation changes." This was the last time that Juan appeared in the organizing notes, suggesting either that Juan left his job or that the organizers gave up on trying to bring him around. In our dataset, Juan was referenced in nine organizer notes by the end of the campaign, and he had a network centrality score of

0, the lowest possible, indicating either a lack of workplace relationships or a lack of organizer awareness of those relationships.

Around the same time that the organizers met Juan, though, they also met Dora Avila; according to Dora, one of the OUR organizers was dating her ex-brother-in-law, and they started talking about OUR Walmart over a coffee at Starbucks. After the meeting, the organizer wrote that Dora had been working at Walmart for five-years and had a well-defined set of grievances: Walmart would cut people's hours and change their shifts arbitrarily; the managers would show favoritism to some workers over others, often in a way that reeked of sexism; and the company made her pay $160 a month out of pocket for health care. She was the fourth worker to sign up for the organization in the Pico Rivera store, but would quickly become one of the most essential.

Having identified Dora as a potential leader, organizers began to meet consistently with her to give her support and guidance as she reached out to her coworkers. Ten days after an organizer met with Dora for the first time, Dora brought a second worker (Lourdes) to a meeting with another organizer at a nearby shopping center. Lourdes signed up for the organization at that meeting, representing the first time that a sign-up occurred through the efforts of a worker leader at the store.

Dora soon proved that she could recruit her coworkers to the organization in a way that organizers could not. This was not just because she knew who they were and how to reach them, but also because she was respected by her coworkers and thus able to influence them in ways that organizers could not. For instance, on December 7, an organizer had approached Lorena, who worked in the bakery department (25 organizer notes and the 67th percentile of network centrality). In that meeting, Lorena had not been sure about the organization: on the one hand, she wanted "more help," and "more respect" from Walmart; on the other hand, she was "very scared" that she was "going to lose her job." A month later, though, on January 12th, Dora was able to convince Lorena to come to an organizing meeting. At this meeting, she "got her to sign."

Dora was clearly central in the social network of potential supporters at Pico Rivera; we see this both anecdotally and through the database statistics, in which Dora has the highest network centrality at the store. Most importantly, organizers from OUR Walmart seemed to recognize and nurture this centrality, providing Dora with support, advice, and encouragement as she took on and completed assignments to reach out to those with whom she was connected. On February 9th, Dora set up an organizing meeting with five of her coworkers. On March 18th, Dora led a meeting at the local Shakey's Pizza, where three more of her coworkers signed up for the organization. In the meantime, organizers were regularly in touch with Dora, strategizing with her about recruitment; putting her in touch with journalists who were beginning to cover the campaign; inviting her to meetings and trainings. As Dora organized among her coworkers, organizers increasingly invested time in supporting her. Excluding notes recording connections that Dora had made with others, organizers recorded 138 conversations or meetings with Dora individually over the course of the 2.5 year campaign.

We see a similar pattern in the way that OUR Walmart identified and developed another key leader at the Pico Rivera Store, Michelle Rogers. As documented in Reich and Bearman (Reich and Bearman, 2018, pp. 167-168), Michelle reports that she initially heard about OUR Walmart from "Crazy Dora Avila." As Michelle recalls, "She was always asking me, 'Hey, mama, how's things going?' And I would tell her, 'Not good,' you know... And she would say, 'You know, when we get a chance, let's talk.'" The two met at a Del Taco, a nearby fast-food joint, where Dora introduced Michelle to some of the OUR Walmart organizers. Michelle went home and looked up the organization online. She concluded that "if I was going to have to be here for a few more years," she would have to "either make changes or just take the beatings." She signed up for the organization on February 12, 2011. Michelle herself was well-connected in the store, in the 99th percentile of network centrality based on organizer notes.

In those early months, Michelle attended a few meetings, but did not do much more than pay the organization's monthly dues. In July, however, an organizer sat her down to encourage her to be more active in the organization. Specifically, the organizer asked that Michelle take on two "assignments" to speak with coworkers she knew about OUR Walmart. It took a number of months, and concerted attention from an organizer, but Michelle eventually committed to the organizing process, with friends. When it became clear that Michelle was connected to others and able and willing to reach out to them, organizers invested more in her. Between late 2010 and February of 2012, organizers reported only six conversations with Michelle. Between

February 2012 and mid-2014, organizers reported 46.

Through the identification and development of leaders like Dora and Michelle, which involved attention to their network relationships, OUR Walmart organizers at Pico Rivera were able to build an active committee of workers open to taking collective action. We next turn to a case where the organizers did not make use of a network-driven organizing strategy to illustrate the alternative, before moving to our quantitative evidence, to test the relationship between network-driven organizing and campaign success across many stores.

Before we do so, however, we want to underscore how difficult it is to organize at Walmart, even when workers are invested in doing so: Walmart seemed to recognize the threat posed by workers at the Pico Rivera store. In April of 2015, the company announced that there was a plumbing problem at Pico Rivera, and that it would have to shut down and layoff its workforce. When it reopened six months later, those most active in OUR Walmart were not rehired.

4.2 Organizing without the Network

The campaign at the Federal Way Walmart, outside of Tacoma, Washington, shared several features with the Pico Rivera campaign. Based on organizer effort (indicated by total number of notes logged by organizers), the campaigns were practically equivalent: organizers at Federal Way logged 1,350 notes over the course of the campaign, only about seven percent less than the 1,448 notes logged at Pico Rivera. At Federal Way, organizers were in contact with more workers than they were at Pico Rivera: organizers logged notes about 326 workers at Federal Way (94% of all store contacts), compared to just 170 at Pico Rivera (55% of store contacts). At Federal Way, though, organizers did not seem to make use of networks among workers in the same way as they did at Pico Rivera: although they did use organizing conversations to map the shop's social network, they used this social network to reach uncontacted workers themselves, rather than to prioritize their relationship with central workers, who had a greater capacity to influence their coworkers. Ultimately, organizers at Federal Way managed to sign up 83 workers for the organization, or 25% of their contacts. At Pico Rivera, organizers managed to sign up 118 workers for the organization, or 38% of store contacts, a success rate nearly 60% higher. One reason for this difference in success rate seems to be the different strategies deployed by organizers in the two stores.

Early in the campaign at Federal Way, organizers seemed to identify several workers who were central in the workplace network; people who provided organizers with the names of other potential supporters. And yet organizers did not seem to follow up with these workers, or support them in their efforts to reach out to others. For instance, in June of 2011, a worker named Daniel (9 notes, 97th percentile of network centrality) convinced a coworker named Eleanor Bernard (6 notes, 82nd percentile of network centrality) to sign up. Organizers had approached Eleanor earlier that year, in April, but she had demurred on participating in the organization because "she might be quitting soon and [Walmart wasn't] important to her." But Daniel had persuaded her, illustrating that co-worker persuasion was present at Federal Way, even though organizers were not focusing their efforts on the network.

After Eleanor signed up, she seemed to have the potential to be Federal Way's Dora Avila. She made efforts to introduce coworkers to organizers and she was in the 99th percentile of network centrality in the store. On June 30, 2011, as organizers waited outside her store, Eleanor convinced three coworkers to meet with them outside on their breaks. Just as some workers at Pico Rivera refused to talk to organizers but were willing to talk to Dora, several of Eleanor's coworkers refused to talk to anyone but Eleanor. In early August of 2011, she gathered a group of workers outside her store to sign a declaration of principles. And then Eleanor disappears from the notes—-organizers apparently stopped having conversations with her; they also did not note that she had cooled on the organization. The next note about Eleanor occurred on March 5, 2012, seven months after the declaration of principles, when her membership dues lapsed because her credit card was declined. She is recorded as having attended one final meeting a week later, on March 12th, and then she disappears from the notes again. The final note about her (out of a total of 6 notes), in January of 2013, records that she had been inactive for six months and was now opposed to the organization.

This seemed like something of a pattern at the Federal Way store. In early 2011, organizers stopped by the house of Erik Fraser, who expressed interest in the organization. Between July and October of that year, he provided organizers with information about fifty-six of his coworkers, reflecting his 100th percentile of network centrality. And yet organizers did not meet regularly with Erik, or support him in reaching out to his coworkers. While Erik is logged as having walked out on strike during a national action in November of 2012, there are few recorded meetings or conversations with him (a total of 8 notes). By September of 2013 he had left his job at Walmart. Similarly, Marla Alexander was very active in October and November of 2011, identifying potential leaders and coming to meetings. Based on organizer records, she was in the 99th percentile of network centrality. Then, somewhat abruptly Marla disappears from the log after 10 organizer notes.

In all three cases—-Eleanor, Erik, and Marla—-organizers identified workers who were interested in OUR Walmart and who had a large number of relationships with their coworkers. However, organizers did not record efforts to cultivate these potential leaders through meetings or through encouraging them to talk with their coworkers. Though the organizers expended a lot of effort and made contact with a large number of workers, they did not seem to use network-driven organizing at Federal Way.

Again, we turn to the network graphs to summarize the differences between the two campaigns. In Figure 4, the organizer-recorded network of Pico Rivera workers is on the top and the Federal Way network is on the bottom. The Pico Rivera graph, besides showing a high number of workers who signed an OUR card, clearly shows more organizer notes for the more central workers. In contrast, the Federal Way graph shows no differential investment by organizers in the most central workers. Our hypothesis is that this difference in organizer strategy contributes to the low rate of card signing in that store.

The De Groot model of labor organizing in the Appendix formalizes this idea. We assume worker beliefs about the value of signing a card to evolve based on the beliefs of co-workers connected via a workplace network. Organizers can invest effort in persuading particular workers, and as is typical of De Groot models, all workers wind up with the same steady-state consensus belief about the value of signing a card. This steady-state belief is increasing in the dot product of a worker's influence in the social network and the organizer effort, which motivates our network-driven organizing measure below.

5 Regression Specifications

Motivated by these two case studies, we now present regressions examining the full sample of Walmart campaigns. We examine whether campaigns marked by more network-driven organizing (a higher correlation between organizer attention and employee centrality) are more successful, as measured by OUR membership cards signed.

We begin by presenting simple bivariate scatterplots that show our main result. Recall that our primary outcome of interest is log number of cards signed in a workplace within a campaign. For illustration, we normalize the number of cards by two measures of campaign intensity: worker-week and total organizer conversations. In Panel A of Figure 5 we show the log number of cards per worker-week, as a measure of share of workers who sign cards per week, plotted against our network-driven organizing measure. In Panel B we normalize the number of signed cards by organizer effort, as measured by number of total conversations, as an alternative measure. In both panels we see a statistically significant relationship between the measure of network-driven organizing and the number of cards signed per worker-week or per organizer conversation. [FIGURE 5 HERE]

While Figure 5 demonstrates the basic pattern, we turn to ordinary least squares (OLS) regressions to show robustness to various sets of possible confounds. We estimate regressions of the form:

$$log(Cards_j) = \beta NDO_j + X_j'\gamma + \epsilon_j \tag{1}$$

Standard errors are heteroskedasticity-adjusted. While we have a large number of potential control variables and confounders, which we discuss in the next section, our limited sample size imposes a ceiling on the number of degrees of freedom in the regression. Along with controlling for our covariates in a conventional OLS regression, we also control for a parsimonious set of controls in our baseline specification, selected via a double-LASSO procedure (Belloni et al., 2014).

5.1 Control Variables

One set of controls (Worker and Organizer Controls) are factors related to organizer effort and store size: the number of total organizer notes (representing the amount of effort the organizer expended during the campaign, logged), the total number of employees at each store as represented in the organizer notes (logged), and the total number of employees the organizer contacted (logged). A second set of controls (Campaign Length Controls) are indicators for quintiles of campaign length.

A third set of controls (Other Network Statistics) relate to features of the employee networks as represented by the organizer notes about relationships between employees. Here, we consider the mean and variance of centrality (for either degree and eigenvector centrality, depending on the model) for the store-specific network, as well as the mean degree, the number of relationships (edges) in the network, and the average clustering coefficient of the network. By controlling for these characteristics of the network, we attempt to isolate the unique relationship between network-driven organizing and card signing apart from how the organizer understood and represented the characteristics of the store network.

A fourth set of controls (Demographic Controls) includes the gender composition of the store (percent male) and zip code-level characteristics of the area around the store, including the percentage of Black, Latino/a and White residents, and the mean Annual Gross Income. We use these controls to account for the possibility that card-signing rates are related to features of social organization or solidarity for which this demographic information can serve as a proxy.

Finally, we follow procedures established by Belloni et al. ((Belloni et al., 2014)) for LASSO-selection of controls among the above variables. Those LASSO-selected controls are average clustering coefficient of the store network, variance in store network centrality, number of edges in the store network, length of the campaign, logged number of organizer notes, logged number of workers in the store, logged number of workers contacted by the organizer, store percentage male, and zip-code level characteristics of the percentage Black, percentage Latino/a, and average adjusted gross income.

6 Main Results

Our quantitative analysis examines the relationship between our measure of network-driven organizing and card signing at the store-level for 120 stores. Results from estimating equation 1 using various sets of controls to rule out alternative explanations for the relationship are in Table 2. Columns 1-4 are models using eigenvector centrality; columns 5-8 are models using degree centrality. Recent work indicates that when networks are sparse and subject to measurement error, degree centrality may have better finite sample properties than eigenvector centrality (Cai, 2022). The results are very similar in terms of both patterns and magnitudes regardless of centrality measure. [TABLE 2 HERE]

In Columns 1 and 5, we include only the logged number of organizer notes for a store and the logged mean degree (average number of coworker relationships recorded by the organizer within a store) as controls. These are the two variables whose correlation defines the network-driven organizing measure (though without the notes that record coworker relationships); the coefficients on all three variables are positive and significant. Notably, the coefficient on the network-driven organizing variable, regardless of the method of calculating centrality, is positive and significant indicating that the targeting of effort to high-centrality workers is independently related to the number of cards signed in a store.

We display the relationship between store-level network-driven organizing and logged cards signed conditional on controls in a binned scatterplot in Figure 6. We see no clear evidence for a non-linear relationship between the variables. Columns 2 and 6 include a much larger set of controls selected in order to rule out other explanatory factors: 1) the log of workers contacted or mentioned by the organizers, a measure of both organizer effort and the size of the potential pool of workers who can sign a card; 2) the length of the campaign, as longer campaigns should yield more cards signed over time; 3) additional network statistics including the log of the variance of worker centrality, log number of recorded coworker relationships (network edges), and the average clustering coefficient of the coworker network (assessing closed triads in the network, a common measure of degree of clustering) to ensure that the effects are not an artifact of workplace network structure; and 4) store-level gender composition, and the racial composition and average income of the zip-code in which the store is located. [FIGURE 6 HERE]

In this control-saturated model, the adjusted R-squared increases by about 20%, and the coefficient on the network-driven organizing variable falls by around 20%. This parameter instability may suggest some important omitted variables. To explore this further, in columns 3 and 7, we use double-LASSO (Belloni et al., 2014) as a device to select important sets of covariates. The double-LASSO first uses L1-penalization to select control variables that significantly predict logged cards signed, and then uses a separate L1-penalized regression to select variables that predict the network-driven organizing measure. Any variable selected in either of these regressions is included in a final regression, with standard errors adjusted as in

Belloni et al. (2014). Appendix Table A2 provides the variables selected in each regression.

The resulting adjusted R-squared remains virtually identical, at 0.68, but the coefficient on the network-driven organizing measure is now closer to the simple specification in columns 1 and 5. This exercise suggests that once a sparse set of covariates that predict the outcome or the key independent variable are included, there is little parameter instability while the explanatory power remains high.

As an additional check on our basic empirical finding, we conduct a series of non-parametric permutation tests. We construct 500 datasets of 120 stores each, but within each store of N_j workers, we draw N_j workers *with replacement*, to create a placebo store. To create a within-store network, we first include all the edges (relationships) from the original store where both nodes are in the placebo sample. We then create new edges assuming each worker is connected to any replicates of themselves. We then recalculate all our network statistics in the placebo store, including eigenvector centrality, degree centrality, and the correlation of organizer effort and worker centrality. We then estimate equation 1, including controls for each of these datasets, obtaining 500 placebo β. [FIGURE 7 HERE] Panel A of Figure 7 shows the resulting histogram of the placebos, with a vertical line indicating the empirically-derived coefficient. The observed coefficient for the relationship between network-driven organizing and cards signed is well beyond two standard deviations higher than the mean (or 0).

Panel B of Figure 7 shows the same placebo distribution when the number of organizer notes, rather than the network structure, is randomly reshuffled across workers in a store. We create 500 datasets, holding the network fixed but reshuffling the number of organizer notes across workers within a store. While the true coefficient is substantially greater than the mean, it is less than 2 standard deviations away, and so is just under the magnitude required for statistically significance at conventional levels.

Panel C of Figure 7 shows a more traditional permutation test result, where the network-driven organizing scores are randomly reshuffled across stores in each of the 500 datasets. In this placebo distribution the true coefficient is well into the tails of the distribution and looks quite similar to the main OLS specification. Generally, these tests suggest the robustness of the observed relationship between network-driven organizing and card-signing.

Finally, we might wonder whether other organizing strategies work as well as network-based targeting of organizer effort. To explore this, we construct a measure of "mobilizing" (as opposed to organizing). A mobilizing strategy is one where the organizer allocates more effort towards those workers who are most enthusiastic about the organization. We operationalize this via the Spearman correlation between the number of organizer conversations and how early in the campaign the worker was first contacted, with the assumption that those individuals most open to the organization will be willing to talk earlier in the campaign. As in the Federal Way example above, the mobilizing strategy is one where the earliest workers contacted, rather than those most central in the network, continue to receive the bulk of organizer effort.

In Table 3 we add this measure of "mobilizing" to the table.[1] The coefficient on network-driven remains positive and significant, while the mobilizing score, while positive, is somewhat more imprecise as it varies greatly depending on the included controls. The quantitative magnitudes suggest that mobilization may also be an effective strategy, though not as robust as network-driven organizing. [TABLE 3 HERE]

To summarize, regardless of whether centrality is measured using eigenvector or degree, net of the LASSO-selected controls representing organizer effort, store worker network characteristics, and local area demographics, the network-driven organizing measure is positively associated with the number of cards signed in that store over the course of the campaign. When the organizer has more interactions with high centrality workers, the campaign is more successful. For every one unit (standard deviation) increase in the network-driven organizing term (using eigenvector centrality), 26 more cards are signed in the course of a campaign.

While the OLS estimates are still robust, one covariate reduces the magnitude and significance of the coefficient on our network-driven organizing measure: an indicator for the team assigned to organize that store (columns 4 and 8). The fact that significant variation in the network-driven organizing measure is absorbed by the team indicator suggests a candidate for an instrumental variable to more precisely estimate the relationship between network-driven organizing and number of cards signed.

[1]The measure is formally $Corr(Rank(Conversations_i), Rank(\text{Weeks from first contact with i})$

6.1 Instrumental Variables Estimates

We leverage the team organizing strategy as an instrumental variable. While team assignment appears independent of other determinants of organizing success, team organizing strategy is significantly associated with each individual organizer's use of networks in allocating their organizing effort. We thus use the organizing teams to which organizers were assigned to construct an average network-driven organizing team score for each store, leaving out the network-driven organizing measure for the focal store. We can define it formally as:

$$NDO_j^{Team} = \frac{1}{|Team(j)| - 1} \sum_{k \in \{Team(j)/j\}} NDO_k \tag{2}$$

where $Team(j)$ is the team assigned to store j. Thus, the team measure is the average of the network-driven organizing measure of all the other stores being organized by organizers on the same team.

In Appendix Table A3, we provide bivariate regressions with each of our control variables as outcomes, regressed on the instrument, to examine the exogeneity of the team average network-driven organizing score. Only store zipcode percent Black and mean income are correlated with the NDO_j^{Team} variable, out of 15 regressions. Nevertheless, we control for all of these variables, as well as LASSO-selected variables, in the analyses below.

Panel A of Figure 8 shows the basic bivariate binned scatterplot corresponding to the first-stage of the instrument. Though there are only 10 teams, there is considerable variation in the underlying measure, partly driven by the heterogeneity in team size, and the leave-one-out average is significantly correlated with the left-out store's network-driven organizing measure. Because teams were assigned to regions, as we discuss above, it is likely that teams are exogenous to other determinants of organizing success other than their strategic orientation. [FIGURE 8 HERE]

Panels B and C of Figure 8 show the reduced form scatterplots of the transformed cards signed measure against the leave-one-out team average of network-driven organizing. Both show strong and significant associations.

6.2 Specification and Results

In order to examine robustness to a variety of controls, we estimate a series of two-stage least squares regressions. We obtain instrumental variable estimates starting with the first-stage given by:

$$NDO_j = \alpha NDO_j^{Team} + X_j' \gamma + \epsilon_j \tag{3}$$

and reduced form equation given by:

$$log(Cards_j) = \eta NDO_j^{Team} + X_j' \gamma + \epsilon_j \tag{4}$$

The instrumental variable estimate of β will be given by $\widehat{\beta^{IV}} = \frac{\widehat{\eta}}{\alpha}$. The X_j will be the same sets of covariates from equation 1. We report robust standard errors in parentheses, but also team-level clustered standard errors below in square brackets.

Table 4 shows the instrumental variable estimates of β from specifications parallel to those in 2. The F-statistic from the first-stage is reported at the bottom of the table, and shows that the instrument is generally strong across specifications. Columns 3 and 4 of Appendix Table A2 show the variables selected in regressions with the instrument as the outcome. [TABLE 4 HERE]

The results in Table 4 again suggest strong and significant effects of the network-driven organizing measure on cards signed; the estimates are roughly double the size of the OLS effects. An increase in the correlation between organizer effort and worker centrality from 0 to 1 increases the number of cards signed in a store by between 2 and 3 log points, or roughly 40 to 70 cards signed.

In columns 3 and 6, we again use a variant of the double-LASSO procedure, adjusted for the instrumental variable. Following Belloni et al. (2014), we estimate three L1-penalized regressions (with the penalization parameter chosen by 5-fold cross-validation) with different outcomes, and our full set of controls. We look at LASSO regressions for NDO_j, NDO_j^{Team}, and $log(Cards_j)$ as outcome variables. Any control variable selected in any of these 3 regressions is then included in the two-stage least squares regression as a control.

The instrumental variable coefficients are significantly larger than the OLS coefficients. This could be due to measurement error in the network-driven organizing measure, but it could also could be due to a failure of the exclusion restriction in the instrument. Teams may differ in many respects other than the degree of network-driven organizing, and the assignment of teams to stores may not be uncorrelated with other determinants of campaign success. Further, the stores where the organizer practices network-driven organizing more similar to that of their team may be stores where workers are more responsive to network-driven organizing; organizers who do not comply with the standards of their team may have some different information about what would work in their particular store. While we think these instrumental variable estimates of network-driven organizing point towards a causal interpretation, we cannot rule out all possible confounds.

6.3 Interpretation of magnitudes

Our estimates are large, particularly in the instrumental variable specifications. Even taking the 95% lower confidence bar, the estimates imply an increase in the correlation between organizer effort and worker centrality from 0 to 1 increase cards signed by at least 50%.

Are these magnitudes too large to be plausible? Recall that the sample median cards signed is 13, less than 10% of the average Walmart store employment, and likely less if we account for turnover. Thus, these large percentage increases in card signing should be interpreted in light of the low base rate of signing.

7 Conclusion

In contrast to scholarship that asks how social networks condition participation in collective action, here we focus on the way that organizers draw on their understandings of social relationships to shape their organizing practices– organizers as networkers. Building on previous qualitative scholarship on the theory and practice of labor organizing, this paper offers quantitative evidence that labor organizers are more successful when they focus attention on people who are central within a (perceived) workplace network. We also see, however, that pursuing this strategy is not simple. The highest level of network-driven organizing we observe in this data is a correlation of 0.56, suggesting that it may be quite difficult to target effort according to worker centrality. While we have motivated our results with a De Groot model of social influence, other models, including Bayesian updating or strategic interactions, would provide similar predictions. For example, (Galeotti et al., 2021) show that when network games exhibit strategic complements, optimal interventions should invest proportional to eigenvector centrality.

Our results also speak to longstanding comparative questions about the low level of union density in the United States (Eidlin, 2018), and the difficulty in organizing new unions. The magnitudes of the coefficients suggest that network-driven organizing can significantly increase the number of cards signed, but the absence of any lasting organization in these stores (i.e., none of these stores continue to have significant OUR membership or other representation by a worker organization) also indicates the structural constraints faced by organizers.

In our sample, the mean number of cards signed was 23 (about 17% of the mean workers discovered by an organizer) and no store received more than 38% of cards signed (using the baseline number of workers known to the organizer, likely smaller than the actual number of employees). To put these numbers in context, organizing folk wisdom holds that a shop should not file for NLRB elections without more than 65% of a unit having signed cards because employer opposition mounted during the election period can effectively cut down support by 15%, on average. While using networks in the organizing process can drastically improve organizing outcomes, even the most perfect network-based targeting is unlikely to move enough workers to reach a majority, let alone the 65% threshold. While strategic use of workplace networks important, then, it is unlikely to drive organizing success on its own, highlighting the structural disadvantage organizers face in the high-turnover, low-wage environment of U.S. retail. How these findings and their implications would play out in this more recent period of post-pandemic low unemployment remains an open question.

We are able to analyze the relationship between organizer practice and organizing outcomes because of the uniquely rich relational data collected by organizers over the course of the OUR Walmart organizing campaign. This type of data is increasingly collected by labor organizations in a manner even more systematic and precise than the way OUR collected their data. While OUR was not a traditional labor organization, nor aiming for a traditional NLRB election, the results in this paper are relevant to a variety of organizations aiming to leverage social networks for solving collective action problems. In this sense, our paper contributes to a pragmatist approach to social science that attempts to understand the social world through the lens of solving real-world problems (Prasad, 2021). Spending more time with those workers perceived as central in a workplace yields better organizing outcomes, reflecting that organizers can both leverage and build relationships in a workplace. Our metric of network-driven organizing could be one that workplace-based organizations use to measure and improve their own practice. Other research might compare workplace networks from the perspective of workers to those perceived by organizers. Future partnerships could embed experimental variation in organizer strategy to examine external validity and robustness of the results from this paper.

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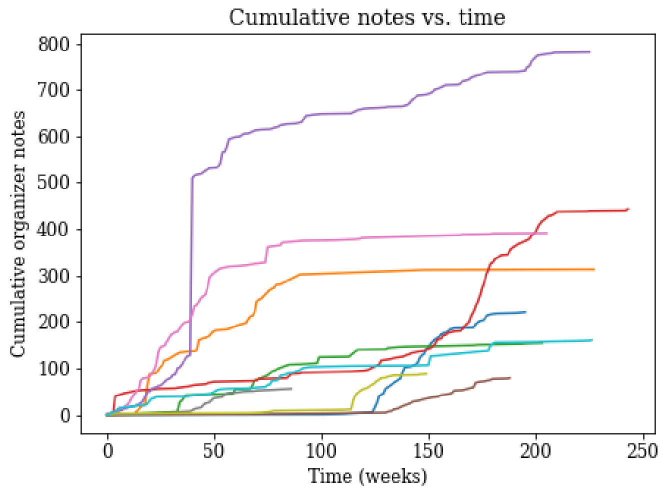
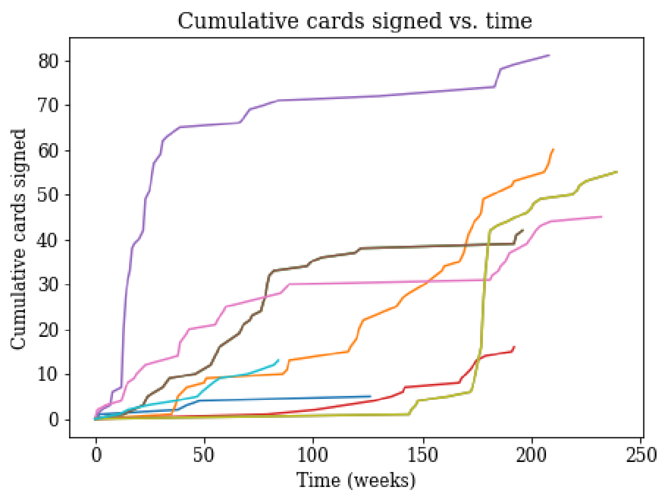
8 Figures

Figure 1: Organizing Activity Over Time



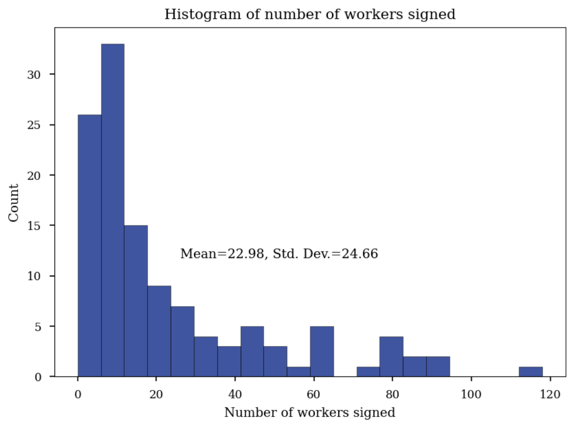
Cumulative organizer notes over time for ten randomly selected stores in sample.



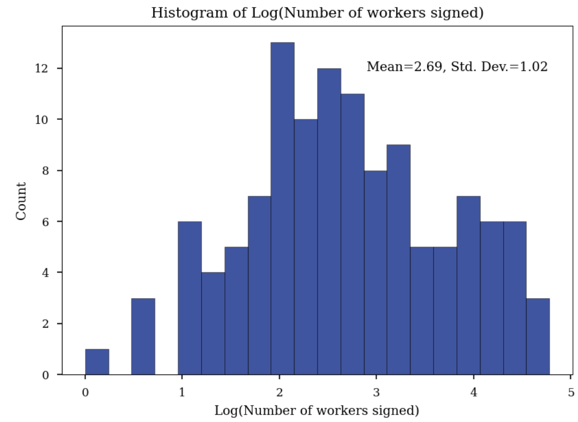
Cumulative membership cards signed over time for ten randomly selected stores in sample.

Organizing activity as measured through organizer notes and membership cards signed.

Figure 2: Signed Cards Measure



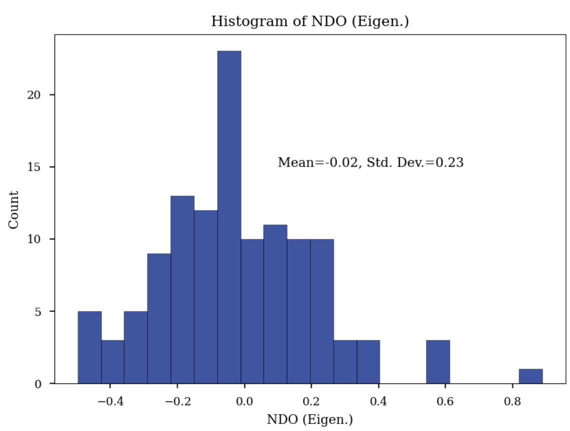
Histogram of number of cards signed.



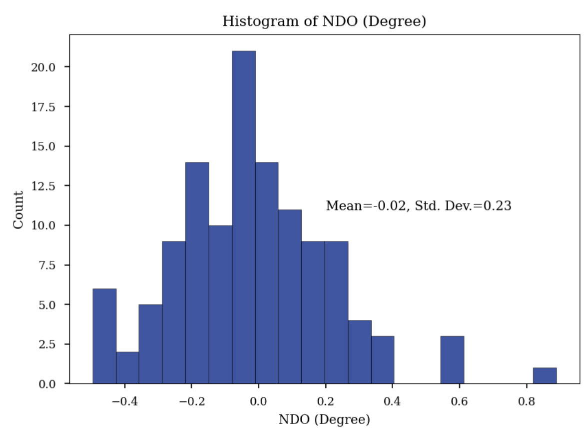
Histogram of number of cards signed (log-transformed).

Distributions of outcome variable, number of cards signed. Variable log-transformed in the main regression to reduce skewness.

Figure 3: Network-Driven Organizing (NDO) Measure



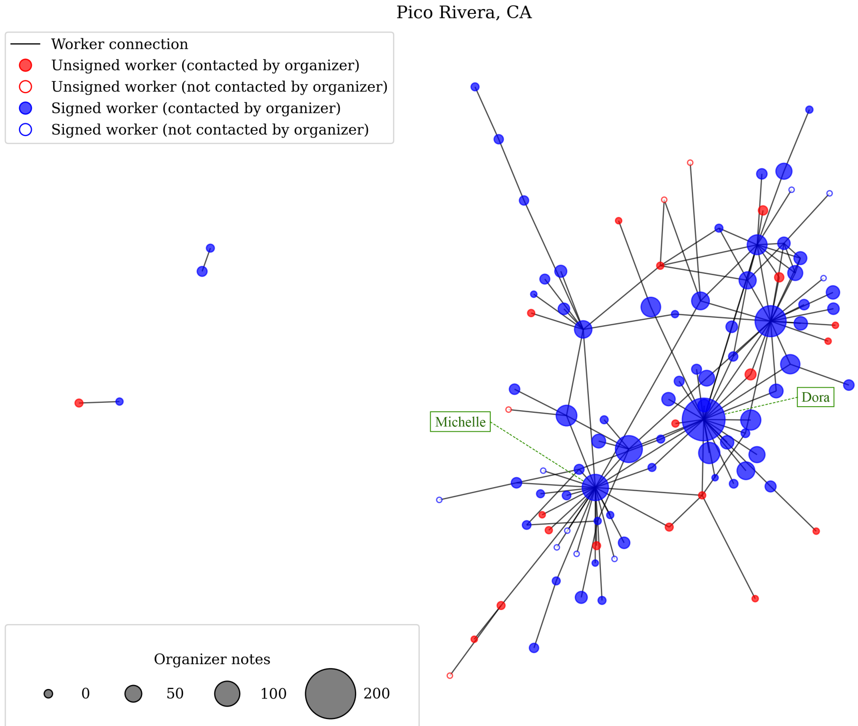
NDO using eigenvector centrality.



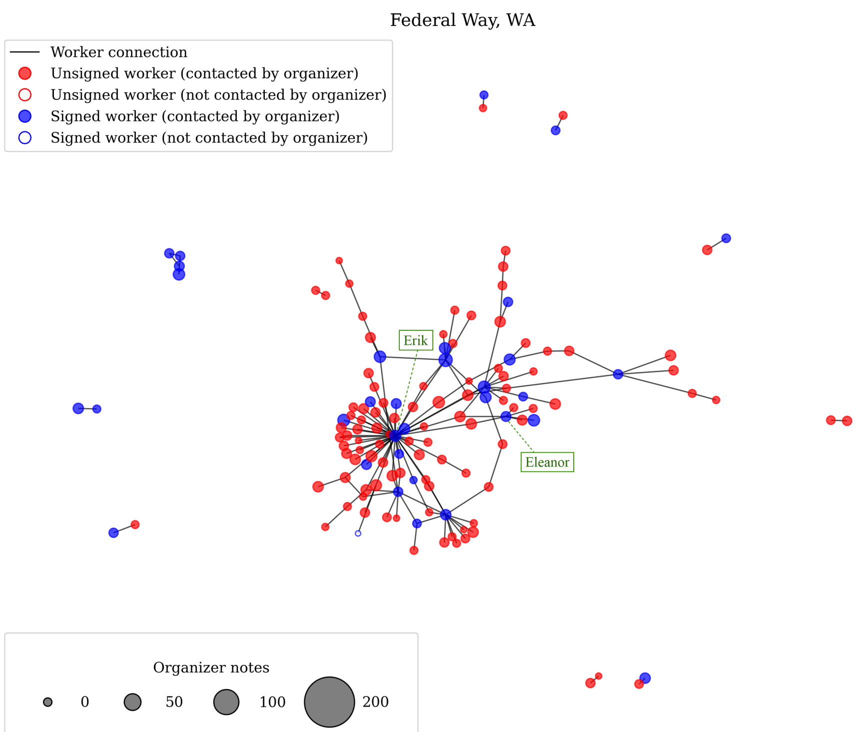
NDO using degree centrality.

Distributions of networked organizing scores using the two selected centrality measures.

Figure 4: Pico Rivera and Federal Way Workplace Networks

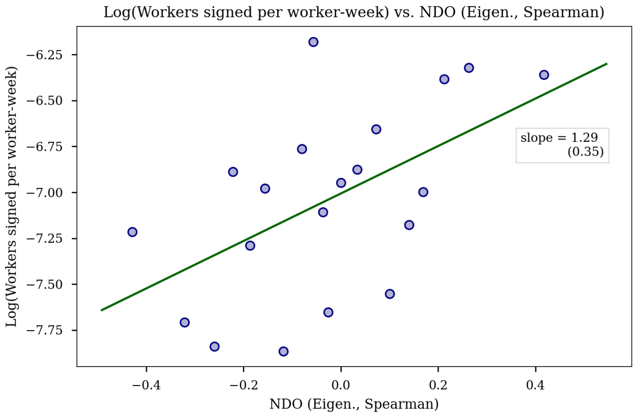


Workplace network from Pico Rivera, CA.

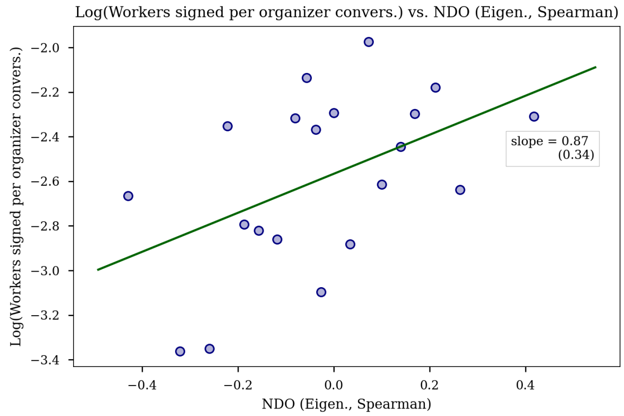


Workplace network from Federal Way, WA.

Figure 5: Cards Signed and Network-Driven Organizing (NDO), No Controls

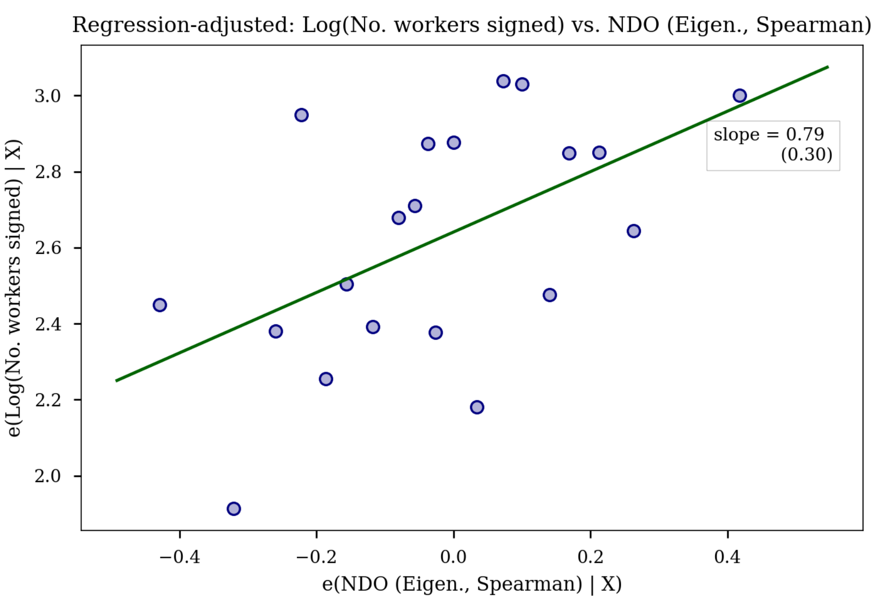


Logged number of cards signed per worker-week vs. Eigenvector network-driven organizing measure.



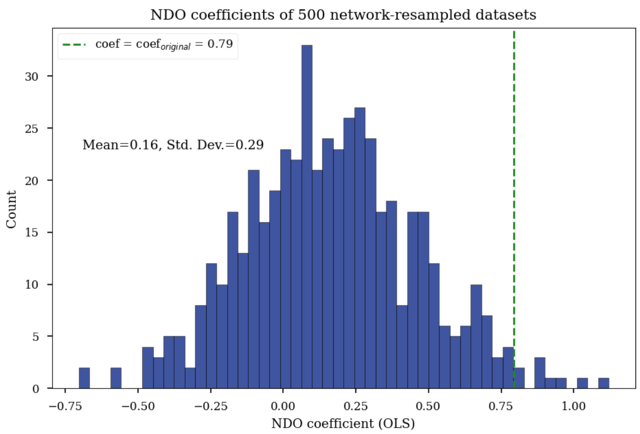
Logged number of cards signed per organizer note vs. Eigenvector network-driven organizing measure.

Figure 6: Cards Signed and Network-Driven Organizing (NDO), Regression Adjusted

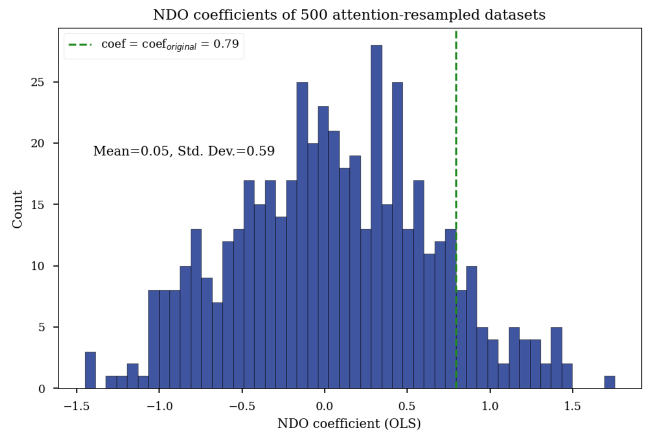


Scatter plot of network-driven organizing vs. logged number of cards signed, conditional on all controls in Table 1.

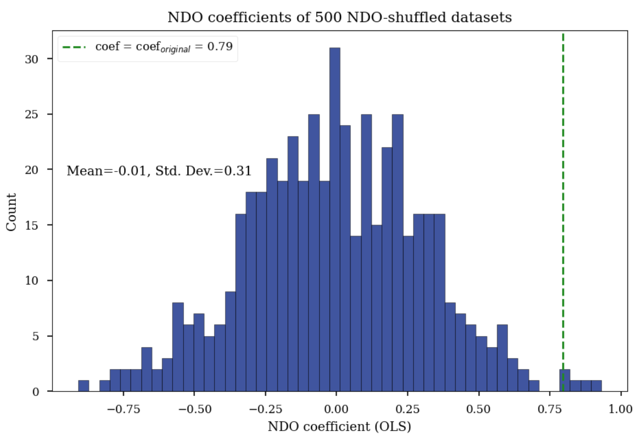
Figure 7: Permutation Tests



Panel A: Distribution of coefficients in regressions with re-sampled networks.



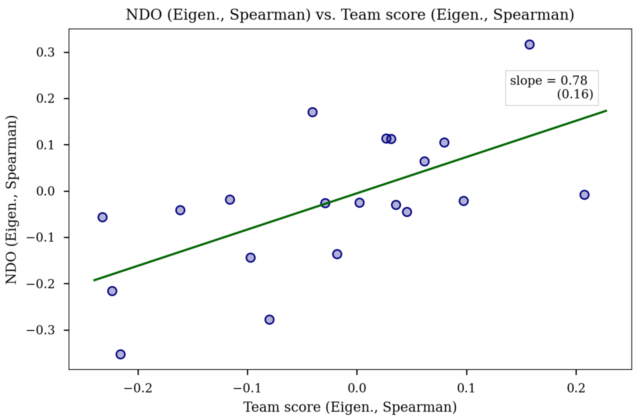
Panel B: Distribution of coefficients in regressions with re-sampled organizer attention.



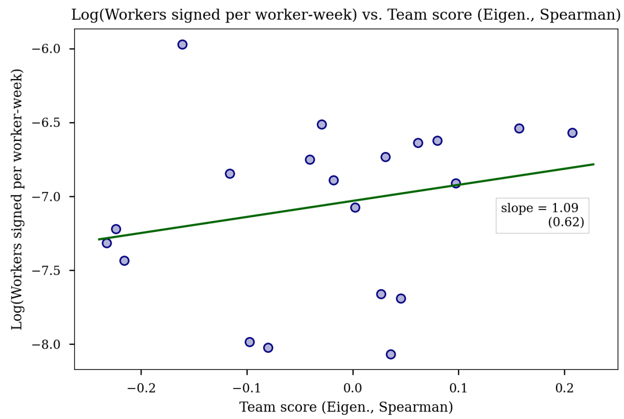
Panel C: Distribution of coefficients in regressions with re-sampled NDO scores.

Distributions of OLS coefficients, regressing logged number of cards signed on network-driven organizing, conditional on all controls in Table 1. Panel A is based on 500 datasets generated by randomly sampling (with replacement) nodes from the original networks to produce networks with the same number of workers and organizer conversations, with random network structures. Panel B is based on 500 datasets generated by holding the network structure constant in each store but randomly permuting the number of organizer conversations across workers. Panel C is based on 500 datasets generates by reshuffling the network-driven organizing score across workers.

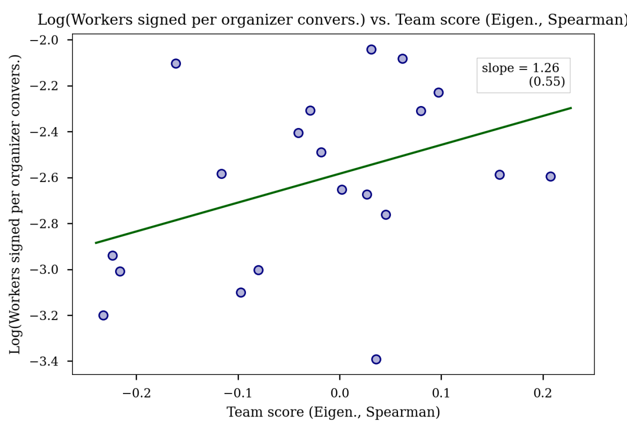
Figure 8: Leave-One-Out Network-driven Organizing (NDO) Team Score Instrument, No Controls



First stage: Eigenvector network-driven organizing measure vs. leave-one-out eigenvector network-driven organizing team score.



Reduced form: Logged number of cards signed per worker-week vs. leave-one-out eigenvector network-driven organizing team score.



Reduced form: Logged number of cards signed per organizer note vs. leave-one-out eigenvector network-driven organizing team score.

9 Tables

Table 1: Store-level Summary Statistics

	Mean	Median	Std. Dev.	Min	Max
No. Organizer Convers.	268.80	181.00	253.59	9.00	1416.00
No. Workers Discovered	136.14	91.50	133.62	11.00	946.00
No. Workers Contacted	102.14	66.50	116.34	7.00	793.00
Campaign Length	178.91	201.43	57.39	22.14	251.14
Mean Network Degree	0.16	0.11	0.15	0.00	0.78
No. Network Edges	18.12	9.00	26.29	1.00	141.00
Variance in Network Centrality	0.00	0.00	0.00	0.00	0.01
Average Network Clustering Coefficient	0.01	0.00	0.03	0.00	0.13
Percent Black in ZIP	0.16	0.07	0.22	0.01	0.98
Percent Latino in ZIP	0.26	0.18	0.24	0.01	0.93
Mean Adjusted Gross Income in ZIP	41.94	38.08	19.07	21.58	141.08
Percent Male	0.40	0.41	0.10	0.00	0.64
Network-driven Organizing (Eigen., Spearman)	-0.02	-0.03	0.21	-0.50	0.56
Network-driven Organizing (Degree, Spearman)	-0.03	-0.03	0.21	-0.50	0.56
Network-driven Organizing (Eigen., Pearson)	0.05	0.05	0.36	-0.68	0.86
Network-driven Organizing (Degree, Pearson)	0.07	0.10	0.41	-0.83	0.92
No. Workers Signed	23.38	13.00	24.56	1.00	118.00

N = 120. Summary statistics for all variables utilized in regressions.

Table 2: OLS Regression of Card Signing on Network-Driven Organizing

	1	2	3	4	5	6	7	8
Network-Driven Organizing	**1.07**	**0.79**	**0.87**	**0.69**	**1.05**	**0.80**	**0.87**	**0.71**
	(0.34)	(0.30)	(0.31)	(0.34)	(0.33)	(0.30)	(0.31)	(0.35)
Log(No. organizer convers.)	**0.82**	**0.48**	**0.50**	0.36	**0.83**	**0.47**	**0.49**	0.35
	(0.08)	(0.19)	(0.20)	(0.22)	(0.08)	(0.19)	(0.20)	(0.22)
Log(Mean degree)	**0.29**	95.62	**0.76**	114.58	**0.29**	92.20	**0.76**	113.26
	(0.05)	(81.06)	(0.19)	(99.79)	(0.05)	(81.19)	(0.19)	(99.52)
LASSO-selected	N	N	Y	N	N	N	Y	N
Centrality metric	Eigen.	Eigen.	Eigen.	Eigen.	Degree	Degree	Degree	Degree
Worker and Organizer Controls	N	Y	Y	Y	N	Y	Y	Y
Campaign Length Controls	N	Y	Y	Y	N	Y	Y	Y
Other Network Statistics	N	Y	Y	Y	N	Y	Y	Y
Demographic Controls	N	Y	Y	Y	N	Y	Y	Y
Team Fixed Effects	N	N	N	Y	N	N	N	Y
Adjusted R_{sq}	0.56	0.66	0.66	0.69	0.56	0.66	0.66	0.69
N_{obs}	120	120	120	120	120	120	120	120

Results of regression of network-driven organizing metrics on number of cards signed, with various controls. No. workers includes logged number of workers ever contacted and logged number of workers referenced in field notes. Campaign length controls are indicators for quintiles of campaign length. Other network statistics include the log of the variance of worker centrality, logged number of edges, and average clustering coefficient. Standard errors are robust, and coefficients significant at 95% are in bold text.

Table 3: OLS Regression of Card Signing on Network-Driven Organizing, Including Endogenous Mobilizing Score

	1	2	3	4	5	6	7	8
Network-driven Organizing	**0.76**	**0.77**	**0.79**	**0.68**	**0.74**	**0.78**	**0.79**	**0.70**
	(0.34)	(0.30)	(0.30)	(0.34)	(0.33)	(0.30)	(0.30)	(0.35)
Mobilizing (Spearman)	**0.88**	0.71	0.63	0.17	**0.87**	0.71	0.63	0.17
	(0.35)	(0.45)	(0.35)	(0.39)	(0.35)	(0.45)	(0.35)	(0.39)
Log(No. organizer convers.)	**0.85**	**0.42**	**0.43**	0.36	**0.85**	**0.41**	**0.42**	0.35
	(0.08)	(0.20)	(0.20)	(0.22)	(0.08)	(0.20)	(0.20)	(0.22)
Log(Mean degree)	**0.32**	66.77	**0.60**	106.50	**0.32**	63.42	**0.60**	105.27
	(0.05)	(90.58)	(0.16)	(107.64)	(0.05)	(90.72)	(0.16)	(107.34)
LASSO-selected	N	N	Y	N	N	N	Y	N
Centrality metric	Eigen.	Eigen.	Eigen.	Eigen.	Degree	Degree	Degree	Degree
Worker and Organizer Controls	N	Y	Y	Y	N	Y	Y	Y
Campaign Length Controls	N	Y	Y	Y	N	Y	Y	Y
Other Network Statistics	N	Y	Y	Y	N	Y	Y	Y
Demographic Controls	N	Y	Y	Y	N	Y	Y	Y
Team Fixed Effects	N	N	N	Y	N	N	N	Y
Adjusted R_{sq}	0.58	0.66	0.67	0.69	0.58	0.66	0.67	0.69
N_{obs}	120	120	120	120	120	120	120	120

OLS regression showing the effects on card signing of various control groups. Spearman Mobilizing score calculated as correlation between the order in which workers are first contacted and the number of organizing conversations they are allocated.

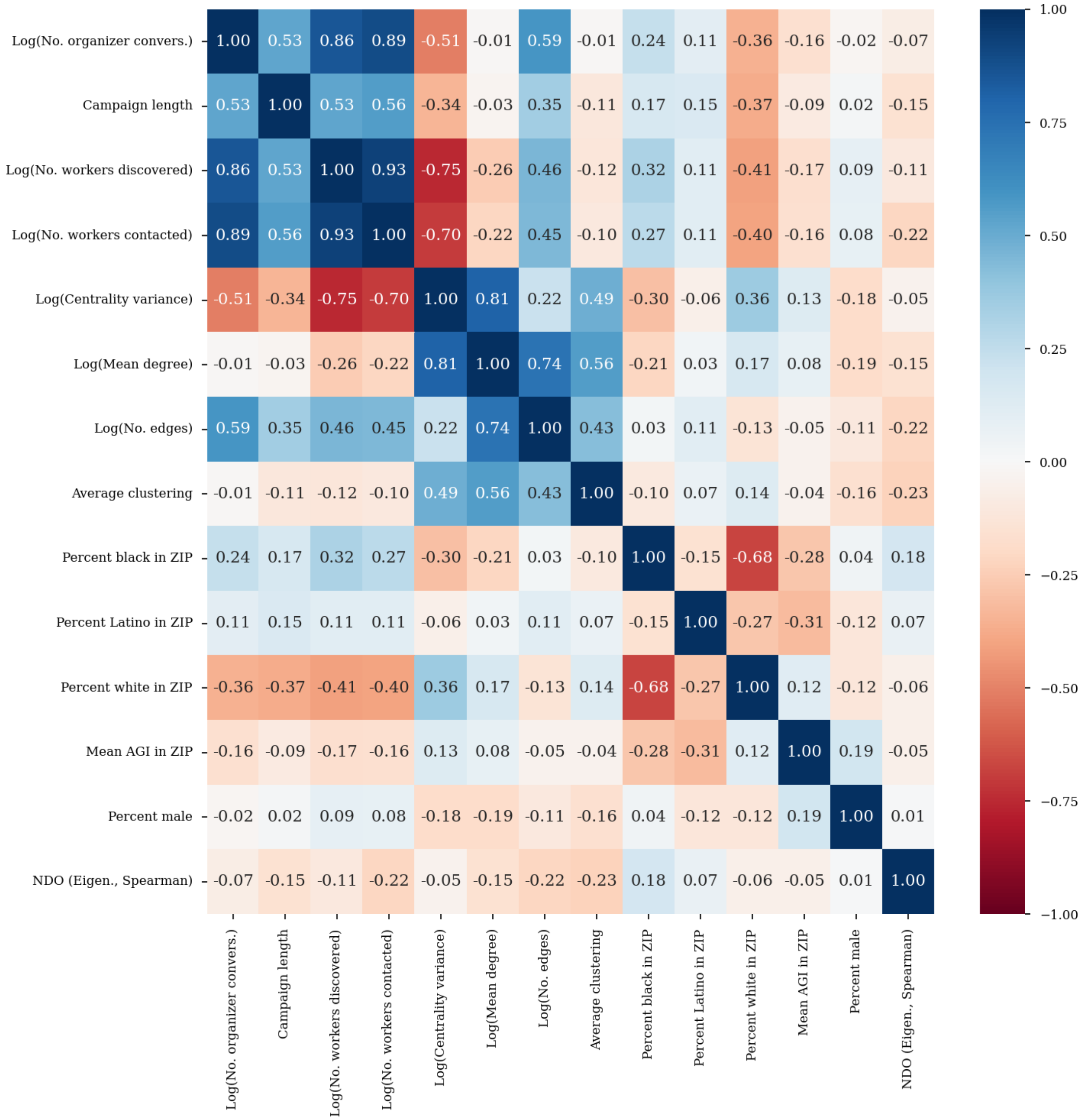
Table 4: Instrumental Variable Regression Results

	1	2	3	4	5	6
Network-driven Organizing	**1.82**	1.69	**1.62**	3.03	1.46	**1.40**
	(0.71)	(0.90)	(0.82)	(2.92)	(0.77)	(0.70)
	[1.01]	[0.53]	[0.48]	[4.67]	[0.45]	[0.40]
Log(No. organizer convers.)	**0.84**	0.37	0.41	**0.80**	0.40	**0.45**
	(0.08)	(0.24)	(0.23)	(0.10)	(0.22)	(0.22)
	[0.07]	[0.29]	[0.28]	[0.13]	[0.28]	[0.26]
Log(Mean degree)	**0.30**	29.32	**0.72**	**0.29**	38.52	**0.71**
	(0.06)	(112.41)	(0.18)	(0.08)	(106.95)	(0.18)
	[0.06]	[91.19]	[0.15]	[0.08]	[85.38]	[0.15]
LASSO-selected	N	N	Y	N	N	Y
Centrality metric	Eigen.	Eigen.	Eigen.	Degree	Degree	Degree
Worker and Organizer Controls	N	Y	Y	N	Y	Y
Campaign Length Controls	N	Y	Y	N	Y	Y
Other Network Statistics	N	Y	Y	N	Y	Y
Demographic Controls	N	Y	Y	N	Y	Y
First-stage F-Stat (Robust)	25.69	9.76	10.48	39.51	13.75	14.90
First-stage F-Stat (Clustered)	75.72	13.53	13.90	314.75	17.99	18.40
Adjusted R_{sq}	0.55	0.64	0.65	0.40	0.65	0.65
N_{obs}	118	118	118	118	118	118

Results of regressions using the leave-on-out networked organizing team score as an instrument, showing the effects of network-driven organizing on the log of cards signed, with various controls. The leave-one-out network-driven organizing team score is calculated as the mean of a store's associated regional stores' (based on teams of organizers) scores, excluding the score of that store. No. workers includes logged number of workers ever contacted and logged number of workers referenced in field notes. Campaign length controls are indicators for quintiles of campaign length. Other network statistics include the log of the variance of worker centrality, log number of edges, and average clustering coefficient. Standard errors are robust, and coefficients significant at 95% are in bold text.

10 Appendix

Figure A1: Variable Correlation Heatmap



Pearson correlation between pairs of indicator variables used in regression analysis.

Table A1: OLS Results (Pearson correlation)

	1	2	3	4	5	6	7	8
Network-driven Organizing	**0.58**	**0.37**	**0.42**	0.33	**0.50**	**0.37**	**0.41**	0.36
	(0.21)	(0.17)	(0.17)	(0.22)	(0.18)	(0.16)	(0.16)	(0.22)
Log(No. organizer convers.)	**0.81**	**0.54**	**0.55**	0.41	**0.80**	**0.50**	**0.53**	0.37
	(0.08)	(0.18)	(0.19)	(0.22)	(0.08)	(0.18)	(0.19)	(0.22)
Log(Mean degree)	**0.31**	105.33	51.38	124.50	**0.31**	109.35	**0.77**	137.42
	(0.05)	(83.37)	(69.16)	(100.62)	(0.05)	(82.88)	(0.19)	(100.48)
LASSO-selected	N	N	Y	N	N	N	Y	N
Centrality metric	Eigen.	Eigen.	Eigen.	Eigen.	Degree	Degree	Degree	Degree
Worker and Organizer Controls	N	Y	Y	Y	N	Y	Y	Y
Campaign Length Controls	N	Y	Y	Y	N	Y	Y	Y
Other Network Statistics	N	Y	Y	Y	N	Y	Y	Y
Demographic Controls	N	Y	Y	Y	N	Y	Y	Y
Team Fixed Effects	N	N	N	Y	N	N	N	Y
Adjusted R_{sq}	0.56	0.65	0.65	0.69	0.55	0.65	0.66	0.69
N_{obs}	120	120	120	120	120	120	120	120

Results of regressions showing the effects of network-driven organizing metrics on number of cards signed, with various controls. No. workers includes log number of workers ever contacted and log number of workers mentioned in field notes. Campaign length controls are indicators for quintiles of campaign length. Other network statistics include the log of the variance of worker centrality, logged number of edges, and average clustering coefficient. Standard errors are robust, and coefficients significant at 95% are in bold text.

Table A2: LASSO-selected Variables (Eigen.)

	NDO	Team score	Log(No. workers signed)
Log(No. organizer convers.)	x	x	x
Campaign length (Quint. 1)	x	x	x
Campaign length (Quint. 2)		x	x
Campaign length (Quint. 3)	x		x
Campaign length (Quint. 4)	x		
Log(No. workers discovered)		x	
Log(No. workers contacted)	x	x	x
Log(Centrality variance)	x		x
Log(Mean degree)			x
Log(No. edges)			
Average clustering			
Percent black in ZIP	x	x	x
Percent Latino in ZIP	x		x
Percent male			
Log(Mean AGI in ZIP)	x	x	x

Variables selected by LASSO for the Eigenvector- and rank-correlation-based NDO metric.

Table A3: Instrumental Variable Controls Test

Campaign	A	Network	B	Demographic	C
Log(No. organizer convers.)	-0.01	Log(Centrality Var)	-0.00	Percent Black in ZIP	**0.16**
	(0.01)		(0.00)		(0.03)
	[0.02]		[0.01]		[0.08]
Campaign length (Quint. 1)	0.03	Log(Mean degree)	-0.01	Percent Latino in ZIP	0.01
	(0.03)		(0.01)		(0.04)
	[0.06]		[0.01]		[0.13]
Campaign length (Quint. 2)	0.05	Log(No. edges)	-0.00	Percent male	0.07
	(0.03)		(0.01)		(0.10)
	[0.02]		[0.01]		[0.10]
Campaign length (Quint. 3)	-0.01	Average clustering	0.12	Log(Mean AGI in ZIP)	**-0.06**
	(0.03)		(0.38)		(0.02)
	[0.02]		[0.20]		[0.02]
Campaign length (Quint. 4)	-0.00				
	(0.02)				
	[0.03]				
Log(No. workers discovered)	0.00				
	(0.01)				
	[0.02]				
Log(No. workers contacted)	-0.02				
	(0.01)				
	[0.03]				

IV bivariate coefficients on controls (robust and clustered errors). Spearman correlation.

Table A4: Instrumental Variable First Stage Results (Rank Correlation)

	1	2	3	4	5	6
Team NDO score	**0.76**	**0.53**	**0.55**	**0.79**	**0.57**	**0.59**
	(0.15)	(0.17)	(0.17)	(0.14)	(0.15)	(0.15)
	[0.09]	[0.16]	[0.16]	[0.08]	[0.15]	[0.15]
Log(No. organizer convers.)	-0.01	**0.15**	**0.16**	-0.01	**0.16**	**0.16**
	(0.02)	(0.04)	(0.04)	(0.02)	(0.04)	(0.04)
	[0.02]	[0.04]	[0.05]	[0.02]	[0.04]	[0.05]
Log(Mean degree)	-0.02	41.31	-0.02	-0.02	41.21	-0.01
	(0.01)	(28.52)	(0.06)	(0.01)	(27.95)	(0.06)
	[0.02]	[45.04]	[0.07]	[0.02]	[44.10]	[0.07]
LASSO-selected	N	N	Y	N	N	Y
Centrality metric	Eigen.	Eigen.	Eigen.	Degree	Degree	Degree
Worker and Organizer Controls	N	Y	Y	N	Y	Y
Campaign Length Controls	N	Y	Y	N	Y	Y
Other Network Statistics	N	Y	Y	N	Y	Y
Demographic Controls	N	Y	Y	N	Y	Y
Adjusted R_{sq}	0.21	0.35	0.33	0.25	0.39	0.37
N_{obs}	118	118	118	118	118	118

Results of first-stage regressions, showing the effects of leave-one-out team scores on network-driven organizing metrics, with various controls. The leave-one-out network-driven organizing team score is calculated as the mean of a store's associated regional stores' (based on teams of organizers) scores, excluding the score of that store. No. workers includes logged number of workers ever contacted and logged number of workers referenced in field notes. Campaign length controls are indicators for quintiles of campaign length. Other network statistics include the log of the variance of worker centrality, log number of edges, and average clustering coefficient. Standard errors are robust, and coefficients significant at 95% are in bold text.

Table A5: Instrumental Variable Reduced Form Results (Rank Correlation)

	1	2	3	4	5	6
Team NDO score	**1.39**	0.89	0.89	**1.29**	0.83	0.83
	(0.51)	(0.47)	(0.46)	(0.48)	(0.44)	(0.43)
	[0.84]	[0.34]	[0.29]	[0.79]	[0.32]	[0.27]
Log(No. organizer convers.)	**0.82**	**0.63**	**0.67**	**0.82**	**0.63**	**0.67**
	(0.09)	(0.20)	(0.20)	(0.09)	(0.20)	(0.20)
	[0.08]	[0.26]	[0.21]	[0.08]	[0.26]	[0.21]
Log(Mean degree)	**0.26**	98.93	**0.69**	**0.26**	98.82	**0.69**
	(0.05)	(90.79)	(0.19)	(0.05)	(90.61)	(0.19)
	[0.07]	[95.04]	[0.20]	[0.07]	[94.74]	[0.20]
LASSO-selected	N	N	Y	N	N	Y
Centrality metric	Eigen.	Eigen.	Eigen.	Degree	Degree	Degree
Worker and Organizer Controls	N	Y	Y	N	Y	Y
Campaign Length Controls	N	Y	Y	N	Y	Y
Other Network Statistics	N	Y	Y	N	Y	Y
Demographic Controls	N	Y	Y	N	Y	Y
Adjusted R_{sq}	0.55	0.65	0.65	0.55	0.65	0.65
N_{obs}	118	118	118	118	118	118

Results of reduced-form regressions showing the effects of leave-one-out network-driven organizing team scores on number of cards, with various controls. No. workers includes logged number of workers ever contacted and logged number of workers referenced in field notes. Campaign length controls are indicators for quintiles of campaign length. Other network statistics include the log of the variance of worker centrality, log number of edges, and average clustering coefficient. Standard errors are robust, and coefficients significant at 95% are in bold text.

Table A6: Instrumental Variable First Stage Results (Pearson correlation)

	1	2	3	4	5	6
Team NDO score	**0.77**	**0.58**	**0.59**	**0.83**	**0.69**	**0.69**
	(0.13)	(0.16)	(0.16)	(0.11)	(0.13)	(0.13)
	[0.09]	[0.16]	[0.15]	[0.06]	[0.17]	[0.14]
Log(No. organizer convers.)	-0.01	**0.18**	**0.21**	0.01	**0.27**	**0.29**
	(0.03)	(0.07)	(0.07)	(0.04)	(0.08)	(0.08)
	[0.04]	[0.11]	[0.11]	[0.05]	[0.12]	[0.11]
Log(Mean degree)	**-0.06**	59.88	13.16	**-0.07**	14.53	0.02
	(0.03)	(45.50)	(45.93)	(0.03)	(49.53)	(0.11)
	[0.02]	[79.70]	[73.15]	[0.03]	[96.64]	[0.14]
LASSO-selected	N	N	Y	N	N	Y
Centrality metric	Eigen.	Eigen.	Eigen.	Degree	Degree	Degree
Worker and Organizer Controls	N	Y	Y	N	Y	Y
Campaign Length Controls	N	Y	Y	N	Y	Y
Other Network Statistics	N	Y	Y	N	Y	Y
Demographic Controls	N	Y	Y	N	Y	Y
Adjusted R_{sq}	0.26	0.37	0.34	0.36	0.44	0.43
N_{obs}	118	118	118	118	118	118

Results of first-stage regressions, showing the effects of leave-one-out team scores on network-driven organizing metrics, with various controls. The leave-on-out team NDO score is calculated as the mean of the associated regional team's scores at all stores associated with that team, excluding the focal store. No. workers includes log number of workers ever contacted and log number of workers mentioned in field notes. Campaign length controls are indicators for quintiles of campaign length. Other network statistics include the log of the variance of worker centrality, log number of edges, and average clustering coefficient. Standard errors are robust, and coefficients significant at 95% are in bold text.

Table A7: Instrumental Variable Reduced Form Results (Pearson correlation)

	1	2	3	4	5	6
Team NDO score	**0.79**	0.51	0.52	**0.68**	**0.43**	**0.42**
	(0.29)	(0.27)	(0.28)	(0.22)	(0.22)	(0.21)
	[0.36]	[0.20]	[0.21]	[0.27]	[0.18]	[0.16]
Log(No. organizer convers.)	**0.81**	**0.65**	**0.69**	**0.81**	**0.65**	**0.70**
	(0.08)	(0.20)	(0.20)	(0.08)	(0.20)	(0.20)
	[0.08]	[0.26]	[0.22]	[0.08]	[0.26]	[0.22]
Log(Mean degree)	**0.26**	85.11	28.40	**0.27**	79.01	**0.72**
	(0.05)	(95.10)	(79.23)	(0.05)	(94.64)	(0.19)
	[0.07]	[96.14]	[66.93]	[0.07]	[95.21]	[0.19]
LASSO-selected	N	N	Y	N	N	Y
Centrality metric	Eigen.	Eigen.	Eigen.	Degree	Degree	Degree
Worker and Organizer Controls	N	Y	Y	N	Y	Y
Campaign Length Controls	N	Y	Y	N	Y	Y
Other Network Statistics	N	Y	Y	N	Y	Y
Demographic Controls	N	Y	Y	N	Y	Y
Adjusted R_{sq}	0.56	0.65	0.65	0.56	0.65	0.65
N_{obs}	118	118	118	118	118	118

Results of reduced-form regressions showing the effects of leave-one-out team scores on card-signing, with various controls. No. workers includes log number of workers ever contacted and log number of workers mentioned in field notes. Campaign length controls are indicators for quintiles of campaign length. Other network statistics include the log of the variance of worker centrality, log number of edges, and average clustering coefficient. Standard errors are robust, and coefficients significant at 95% are in bold text.

Table A8: Instrumental Variable Results (Pearson correlation)

	1	2	3	4	5	6
Network-driven Organizing	**1.03**	0.87	0.88	**0.82**	0.62	0.61
	(0.38)	(0.50)	(0.48)	(0.27)	(0.32)	(0.31)
	[0.41]	[0.43]	[0.43]	[0.28]	[0.31]	[0.29]
Log(No. organizer convers.)	**0.82**	**0.49**	**0.50**	**0.80**	**0.49**	**0.52**
	(0.08)	(0.20)	(0.21)	(0.08)	(0.20)	(0.20)
	[0.07]	[0.31]	[0.31]	[0.07]	[0.31]	[0.29]
Log(Mean degree)	**0.33**	32.78	16.82	**0.33**	69.94	**0.71**
	(0.06)	(114.61)	(82.32)	(0.06)	(95.58)	(0.19)
	[0.07]	[112.28]	[84.15]	[0.07]	[89.60]	[0.13]
LASSO-selected	N	N	Y	N	N	Y
Centrality metric	Eigen.	Eigen.	Eigen.	Degree	Degree	Degree
Worker and Organizer Controls	N	Y	Y	N	Y	Y
Campaign Length Controls	N	Y	Y	N	Y	Y
Other Network Statistics	N	Y	Y	N	Y	Y
Demographic Controls	N	Y	Y	N	Y	Y
First-stage F-Stat (Robust)	32.34	13.71	14.28	56.71	26.72	29.96
First-stage F-Stat (Clustered)	88.28	16.59	19.00	191.17	20.34	28.73
Adjusted R_{sq}	0.55	0.64	0.64	0.56	0.65	0.66
N_{obs}	118	118	118	118	118	118

Results of regressions using the leave-on-out team score as an instrument, showing the effects of network-driven organizing metrics on card-signing, with various controls. The leave-on-out team NDO score is calculated as the mean of the associated regional team's scores at all stores associated with that team, excluding the focal store. No. workers includes log number of workers ever contacted and log number of workers mentioned in field notes. Campaign length controls are indicators for quintiles of campaign length. Other network statistics include the log of the variance of worker centrality, log number of edges, and average clustering coefficient. Standard errors are robust, and coefficients significant at 95% are in bold text.

Table A9: Adding Endogenous Mobilizing Score (IV)

	1	2	3	4	5	6
NDO	-12.80	-5.11	1.03	-8.98	-4.36	0.92
	(55.77)	(35.21)	(3.47)	(28.22)	(26.70)	(3.04)
	[46.76]	[30.51]	[2.31]	[24.32]	[22.56]	[2.04]
Mobilizing (Spearman)	24.02	-59.88	-12.85	19.01	-57.04	-12.96
	(90.44)	(253.41)	(15.12)	(49.64)	(215.50)	(14.87)
	[78.78]	[219.20]	[16.03]	[44.98]	[180.92]	[15.56]
Log(No. organizer convers.)	1.46	6.97	1.81	1.33	6.62	1.84
	(2.32)	(28.81)	(1.80)	(1.27)	(24.11)	(1.73)
	[1.97]	[25.58]	[1.81]	[1.14]	[20.87]	[1.73]
Log(Mean degree)	0.97	3097.93	0.76	0.84	2940.69	0.76
	(2.56)	(13331.43)	(0.63)	(1.45)	(11187.76)	(0.63)
	[2.35]	[11531.13]	[0.40]	[1.41]	[9404.49]	[0.40]
LASSO-selected	N	N	Y	N	N	Y
Centrality metric	Eigen.	Eigen.	Eigen.	Degree	Degree	Degree
Worker and Organizer Controls	N	Y	Y	N	Y	Y
Campaign Length Controls	N	Y	Y	N	Y	Y
Other Network Statistics	N	Y	Y	N	Y	Y
Demographic Controls	N	Y	Y	N	Y	Y
NDO First-stage F-Stat (Robust)	26.48	10.29	10.49	32.79	14.00	14.92
NDO First-stage F-Stat (Clustered)	76.29	16.28	14.76	111.26	20.46	19.29
Mob. First-stage F-Stat (Robust)	15.34	0.28	0.90	15.56	0.28	0.92
Mob. First-stage F-Stat (Clustered)	76.53	0.47	0.85	73.13	0.47	0.91
Adjusted R_{sq}	-15.33	-60.92	-2.94	-8.88	-55.05	-3.00
N_{obs}	118	118	118	118	118	118

IV regression showing the effects on card signing of various control groups. Two leave-one-out instruments used for two corresponding endogenous variables (NDO and Mobilizing scores).

A A DeGroot Model of Labor Organizing

We motivate our measure with a canonical framework for network social learning, the DeGroot model (DeGroot (1974)). This is by no means the only motivation, as foundations based on strategic interactions (e.g. Ballester et al. (2006)) could also be given. But based on the qualitative evidence, it seems like social learning is an important mechanism, and we formalize the intuition here.

We suppose the subjective value to worker i of signing a card at time t is given by $v_i(t)$. We further suppose that co-workers in a workplace are strongly connected by a symmetric unweighted graph given by adjacency matrix A, with $A_{ii} = 0$. This network can reflect relationships of trust, Bayesian priors on whose signals to put more weight on, or simply the number of interactions that result in learning at work.

Define the influence matrix induced by A as G, where $G_{ij} = \frac{A_{ij}}{d_i}$ if $i \neq j$ and $G_{ii} = 1$ otherwise (this ensures aperiodicity of the influence matrix), with $d_i = \sum_j A_{ij}$ being the degree of worker i.

In this model, individual workers i update their beliefs about the value of signing a card based on the beliefs of the people they are connected to in the network G. After T periods of learning, with no organizer effort, the subjective value of worker i will be

$$v_i(T) = (G^T v(0))_i$$

In an undirected, connected, and aperiodic network, the steady-state beliefs of everyone in the workplace converge to the same value, given by the dot product of initial beliefs $v(0)$ with the eigenvector of the matrix G corresponding to the eigenvalue of 1 (which is the highest eigenvalue as G is a stochastic matrix), denoted C. In steady-state $v(\infty)_i = C \cdot v(0)$ for all i, i.e. there will be consensus.

It is easy to see that $C_i = \frac{d_i}{\sum_j d_j}$ satisfies $\mathbf{C}'\mathbf{G} = \mathbf{C}$, so that the normalized degree of a worker measures the influence of a worker on co-workers. However also note that any rescaling of C by scalar will also satisfy the equation.

We modify the assumptions of a DeGroot model by including the existence of an organizer. Assume an organizer can choose an allocation of conversation effort e_i, corresponding to how much effort to spend influencing worker i. Conversation effort can increase a worker's subjective value of signing permanently, but at some finite time $t(i)$ by e_i, at a cost of $\frac{C}{2}e_i^2$, reflecting that there are increasing marginal costs to influencing any individual worker. The convex costs to investing effort in a single worker seems to accord with both qualitative evidence on the difficulties of locating the same worker over time as well as the increasing costs for organizers to induce large changes in worker beliefs.

Empirically, our networks are disconnected due to limitations of measurement, so the classic result showing convergence to a consensus distribution **?** may not be applicable. But if we think the connected component is large and aperiodic, the objective function can be approximated by the DeGroot consensus steady-state.

We further assume the organizer aims to maximize the steady-state sum of values, i.e. $\lim_{t\to\infty}\sum_i v_i(t) = \sum_i C_i(v_i(0) + e_i)$. It is then easy to see that steady-state card signing will be maximized where $C \cdot e$ is maximized, and the organizer invests $e_i = \frac{C_i}{C}$ in each worker i. Where organizers invest the most in the most influential workers, the average long-run probability of card signing will be highest.

Why might an organizer care about the sum of subjective values? One reason is that, particularly in the labor organizing context, having as many people as committed to signing possible is the best antidote against the anti-union campaign that begins once the employer learns of the organizing effort, for example when cards are filed with the NLRB. In the OUR Walmart context, more cards means more paying, committed members, and more participation and higher probability of success in workplace collective actions.

Note that the organizer does not necessarily know the true influence vector C_i, but merely sees a signal of it from a partially observed network. Because we only measure the network as observed by the organizer, we can still see that the expected long-run consensus number of cards signed will be maximized by the organizing investing the most effort in the workers they *perceive* to be most influential.

$C \cdot e$ is proportional to the correlation of e_i and C_i within a store. However, since e and C are on arbitrary scales, and the quantitative prediction should hold with any positive rescaling of the vectors, in the empirical work we will use rank correlations, to ensure that our measures are not being driven by any particular normalization. We examine robustness to standard correlations (Pearson) in Appendix Tables A1-A8.

B Examples of Notes

Date	Worker name	Text
11/09/2010	Sofia Torres	10/25/10; Maria house called; card signer; Bakery Dept. Issues: Too much to do with not enough people. Not enough support from supervisors, and they want her to do more. Would cut her hours because she doesn't have open availability, but since it is high demand in the bakery, they haven't cut her hours. - Lopez, R
05/18/2012	Johnny Hughes	Friend of Isabel Garcia - Schneider, D
10/10/2011	Elena Herrera	Liz has worked at wmt 2280 for 4 years ICT Receiving and Inventory. She makes $12.10/hr works FT 7a-4p M-F. Issues: did not receive full raise in July Review ($0.40). They told her it is because she is not a role model. Her husband (Jerry Alberto Gomez, also a member, former) helped her write a letter to her manager after her review in July 2011, but they didn't give her any answer. She is very upset because she said she does too much work and deserves to make $12.30. Store manager Ben asked her to write a list of all of her qualifications and reasons why she deserves her raise. We helped translate list into English and are waiting to hear the results (9/30/11, Emma and Devika) - Farrow, L
11/28/2010	Ian Kimutai	CTW: 3/24/09 - Signed union card. Referred by Charlotte Jansen. Arthur Jones collected card. Loves Obama. Makes $12.39/hr. - Hoang, T

Examples of organizer notes. "Worker name" reflects the worker with whom the organizer had a conversation, and "Date" reflects the date of that conversation. Network edges were drawn to all workers whose names appear in the note's "Text".