Participation in 280 Characters or Less: Estimating Network Structure Effects of Social Media Platforms on Political Participation

by

Rebecca M. Bryan

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Contents

ABSTRACT

This dissertation explores the relationship between social media use and political participation. The three empirical articles contribute to the development of collective action approaches that incorporate social elements, improving the predictive power of these theories. Additionally, the collective action approaches are applied within a virtual environment to take into account society's growing dependence on digital communication technologies. This dissertation focuses on two social media platforms, Facebook and Twitter, and exploits the network structures of these platforms to determine if social pressure motivates participation. I use two data sources to test my hypotheses: a unique dataset composed of public Facebook data and voter registration data from the 2012 US General Election and survey data gathered during the 2011 Egyptian revolution. I find that the social components of online social media platforms matter: online social pressure has a positive, significant impact on political participation. Platforms that possess strong tie network structures such as Facebook create a greater change in protest participation than platforms that encourage a weak-tie network structure, such as Twitter. This effect is also found with voter turnout: as the social pressure in one's Facebook network increases, an individual is more likely to vote. This effect is strongest for young users of social media; they possess high levels of digital socialization compared to older users.

1 INTRODUCTION

This dissertation explores the causal mechanisms that exist between social media use and political participation. This research contributes to the growing literature on how changing communication technologies influence political behavior, focusing on the impact of social networks and social pressure to follow group norms. Innovations in technology have changed the social and political landscape by offering new sources of information and social interaction. Online networks are similar to face to face networks; they consist of social ties between individuals and provide an opportunity for individuals to encounter information (Margetts et al. 2015; Dunbar et al. 2015). The similarities of online and offline networks indicate that many processes present in face-to-face networks or traditional media sources also present themselves in online networks. The literature has made significant progress towards better understanding the internet's role in influencing political behavior. However, much of this focus is on the informational aspects of digital communication technologies. Studies of social media's influence on participation typically focus on the information environment, specifically a platform's ability to reduce barriers to participation by providing low-cost political information and engagement opportunities (Chadwick and Howard 2009; Margetts et al. 2015). This direction is echoed in models of individual choice, which traditionally focus on individual-level variables over social variables (Ostrom 1998; Ostrom 2000; Finkel and Muller 1998a). These models have difficulty explaining political engagement as they cannot overcome free riding, the dominant strategy for individuals who are not motivated by intrinsic incentives (Aldrich 1993; Feddersen 2004; Gerber, Green, and Larimer 2008). Introducing social variables increases the ability of the model to explain participation through social/psychological selective incentives. Social and psychological variables were often excluded or measured incorrectly in prior research due to the difficulty in accessing social questions, both for researchers and survey respondents (Finkel and Muller 1998b; Converse 1966).

Innovations in technology have increased the ability to observe individual behavior, including social interaction and how individuals acquire and use political information. These innovations allow new insights into enduring questions previously inaccessible due to the limitations of traditional data collection techniques. The three chapters explore modifications to collective action theories and the calculus of voting model that have been proposed throughout the literature, finding that the inclusion of social elements improves a model's explanatory power. Additionally, these theories are applied within a virtual environment to take into account society's growing dependence on digital communication technologies. By expanding traditional models of participation to incorporate both social factors and changes to communication technologies, this dissertation contributes to the general understanding of contemporary political behavior.

Internet use encompasses a variety of mechanisms that influence behavior (Farrell 2012). To determine the effect of social factors using publicly available social media data, the social and informational causal mechanisms that play a role in participation must be differentiated. These three papers rely on the network structure of social media platforms to determine whether social influence is available on that platform. This approach has been used prior literature, applying the assumptions of the "strength of strong ties" and "strength of weak ties" hypotheses to online social networks (Valenzuela, Arriagada, and Scherman 2014). The two competing hypotheses organize how the strength of the social tie influences behavior. These processes determine the effect that each tie structure has on political participation: information that promotes coordination is abundant in weak-tie networks, while social pressure to follow group norms is present in strong- tie networks (Granovetter 1973; Centola and Macy 2007; Centola 2010). Platforms such as Twitter promote a weak-tie, information sharing environment, while platforms such as Facebook prioritize the maintenance of strong social ties between users. Through utilizing weak-tie and strong-tie contexts, researchers can test the effects of social pressure and socially supplied information on political behavior using social media data.

Once the effects of variables that target the social aspects of the decision-making process are isolated from the information or cost-reducing elements, a collective action framework is used to model individual decision making. An actor will weigh the costs and benefits of an action and select the strategy that offers the highest payoff (Olson 1965; Ostrom 2000; Lupia and Sin 2003; Finkel and Muller 1998a). Social media can reduce the cost of coordination and promote participation when the barrier to participation is access to information (Chadwick and Howard 2009; Valenzuela, Arriagada, and Scherman 2014). For the individuals who participate in this scenario, the benefit of intrinsic motivations, such as civic duty, outweigh the remaining costs of participation (Ostrom 2000). For actors who do not value intrinsic motivators, lowering the costs associated with participation does not stimulate engagement. In this situation, the individual should choose to free ride. Free riding should be the dominant strategy according to rational choice models, yet researchers observe that many individuals choose to participate (Ostrom 2000). The inclusion of social/psychological selective incentives changes the utilities associated with strategies available to an individual. Social pressure encourages individuals to follow social norms to gain social rewards and avoid social sanctions (Abrams, Iversen, and Soskice 2011; Gerber, Green, and Larimer 2008; Gerber, Green, and Larimer 2010a; Green and Gerber 2010; Cialdini and Goldstein 2004; Panagopoulos 2010; Mann 2010; Gerber, Green, and Larimer 2010b; Davenport et al. 2010; Ostrom 1998; Ostrom 2000). Social rewards outweigh the costs associated with participation. Social sanctions are subtracted from the benefits that an actor would normally receive from free riding. The addition of social incentives to collective action models lowers the utility associated with free-riding and increases the utility associated with participation.

Research in social media and internet use must update at an unprecedented rate due to the changing nature and capabilities of communication technologies. Internet activity can be impersonal, but also offers a gateway to social activities, including social media platforms, online forums, and multiplayer games (Margetts et al. 2015; Chadwick and Howard 2009). Individuals engage in these online platforms to receive and administer social influence (Li 2011). Many interactions may be nonpolitical. However, even nonpolitical social interactions contribute to social capital formation. Social capital development, both online and offline, positively impacts political participation (Kittilson and Dalton 2010; Baumgartner and Morris 2010; Valenzuela, Park, and Kee 2009; Margetts et al. 2015).

Early internet activity tended to be isolated and impersonal, having limited influence on political participation (Nisbet and Scheufele 2002; Han 2008). These outcomes contrast with the effects of interactive technologies that have dominated technology and politics research over the past few years, which focus on the interactive elements of internet use. Rapid changes in the internet's capabilities highlight the importance of developing an overarching theory of internet use that can accommodate its changing state. These chapters aim to address this issue by developing a general theory of digital communication technology that adapts easily to new platforms. These chapters focus on causal mechanisms that explain the relationship between internet use and political outcomes, allowing the theory to remain broadly applicable to a variety of social media platforms and communication technologies. Though this dissertation focuses on the Facebook and Twitter platforms, the causal story applies to any platform whose network structure can be mapped to a strong-tie or weak-tie network. In this dissertation, I combine both 1) the network structure approach using the strong-tie/weak-tie hypotheses and 2) social pressure theories offers an overarching framework that is not outpaced by a rapidly changing digital environment.

Additionally, I will explore the use of new media as an alternative source of data and new methods associated with its analysis. The ability of researchers to harvest and analyze internet data continues to expand, offering new opportunities to test the effects of internet use on politics (Chadwick and

Howard 2009). New data and new techniques have allowed us to investigate behavior furtherand access previously inaccessible mechanisms (Kittilson and Dalton 2010; Dalton and Kittilson 2012). Data collection methods enable social scientists to collect mass amounts of "first -hand" social media data without the need for surveys. Rich data is available on millions of individuals at multiple points in time; researchers can overcome concerns with causal inference and external validity that are often associated with observational and experimental data. The amount of data and the new quantities of interest allow researchers to measure require new approaches and modifications to existing techniques to make this data useful. This dissertation contributes to the literature by investigating variables that can be used to measure social quantities of interest available using social media data.

Overview

Each of the the chapters presented in this dissertation investigate a different element of social media use and political participation. I limit the analysis to social media's impact on two *traditional* forms of political participation, protest and voting. . Online forms of participation have political value; however, social media's impact on offline forms of participation provides a stronger argument for the real-world implications of social media use. The first empirical chapter investigates the use of strong-tie and weak-tie approaches to determining network structure of two social media platforms: Twitter and Facebook. Accessing the different online networks and their impact on protest participation tests the effects of two possible causal mechanisms at play: 1) information transmission enabling participation in collective endeavors and 2) social pressure as a select incentive, encouraging political participation.

The second empirical chapter further investigates the impact of strong-tie social networks. This chapter focuses on the presence of social pressure within an individual's online social networks and how this variable influences an individual's likelihood of voting. Social pressure is included in the

Calculus of Voting model, modifying the rational choice framework to better incorporate behavior concepts. Social pressure serves as a psychological selective incentive, encouraging participation in order to receive social rewards and avoid social sanctions. The social pressure variable in this chapter measures the *level of exposure* to social pressure. This approach provides more information on the causal process than available in the first chapter, which measured broad differences in use between the two platforms.

The final empirical chapter investigates how online social influence should vary due to an individual's level of digital socialization: the effects of online social pressure should be strongest among users who place value on online forms of communication and are highly digitally socialized. Age cohorts are used to represent one's level of digital socialization. Younger individuals who experienced socialization to social media use during their formative years will have high levels of digital socialization, while older users will have low levels of digital socialization.

2 UNDER PRESSURE: SOCIAL PRESSURE AND PROTEST PARTICIPATION DURING THE 2011 EGYPTIAN REVOLUTION

The role of social media in political science research continues to gain attention, yet studies view these platforms in isolation and without regard to their unique impact on political behavior. This study examines both Facebook and Twitter use, focusing on how variations in the underlying structure of their social networks have unique impacts on political participation. I theorize that platforms composed of a network of "strong ties" will have a greater impact on protest participation due to the network's ability to transmit ***social pressure****, a psychological selective incentive. Using survey data gathered during the 2011 Egyptian Revolution, this study tests the impact that Facebook and Twitter use had on individual participation in the protests. Facebook's strong-tie network structure had a greater impact on the level of individual protest participation than did Twitter's weak-tie network structure. This provides evidence that the network structure of a social media platform matters; the nature of the platform(s) that an individual chooses to engage with will impact their level of political participation. Through social pressure as a selective incentive, strong-tie platforms are able to communicate social norms, which have a significant impact on individual political behavior.*

Introduction

Technological changes have significantly altered the assumptions of collective action theory due to changes in the cost of acquiring information and the cost of participation itself (Lupia and Sin 2003). Social media offer new avenues of participation, networking and information sharing (Margetts et al. 2015). These opportunities raise questions about how these platforms influence individual political behavior.

Social media platforms vary in the structure of their social networks. As a result, platforms may have different effects on political behavior, a detail that has not been given much attention in the literature (Valenzuela, Arriagada, and Scherman 2014; Margetts et al. 2015). Characteristics of each network shape the ties that exist between individuals within the network. Social media platforms promote novel features to differentiate their services from each other in order to attract potential users. For example, Facebook requires reciprocity between ties; both users must consent to the relationship before information is shared between them (Valenzuela, Arriagada, and Scherman

2014). This characteristic has resulted in networks of strong social ties as individuals tend to extend/accept friendship requests from users in their primary offline networks. Twitter does not require reciprocity between users, who can access another user's public information without an explicit relationship having been established. This has encouraged a network of weak social ties focused on information distribution.

The recent influx of interactive communication technologies has reduced the cost of participation by supplying easily accessible and up to date information (Mutz and Young 2011). Formal leadership through organizations is no longer required to initiate and achieve collective action (Bimber, Stohl, and Flanagin 2008). The internet has created opportunities for individuals to organize online (Ward and Gibson 2008; Margetts et al. 2015). Social media reduces information costs, making it easier for those already interested in politics to participate (Brundidge and Rice 2010; Margetts et al. 2015; Lupia and Sin 2003). However, I argue that reduced information costs online will not *stimulate* uninterested individuals who have an incentive to free ride. Beyond the mechanism of reduced transaction costs, the social nature of interactive communication technologies raises the possibility that other mechanisms are driving these outcomes. This paper explores *social pressure* as the causal mechanism existing between social media use and behavior outcomes. Individuals receive social pressure from other members of their online network via public or private messages; these messages mimic information one receives from their offline network. This information notifies individuals of the social values and norms within the network. Social pressure offers social rewards for following group norms and threatens those who resist with social sanctions (Abrams, Iversen, and Soskice 2011; Gerber, Green, and Larimer 2008; Gerber, Green, and Larimer 2010a; Green and Gerber 2010; Cialdini and Goldstein 2004; Panagopoulos 2010; Mann 2010; Gerber, Green, and Larimer 2010b; Davenport et al. 2010). Social pressure functions as a selective incentive (Green and Gerber 2010). This mechanism stimulates participation among individuals who would not have participated from reduced information costs alone, overcoming the free rider problem.

The network structure of the social media platform determines the nature of the ties that exist between individuals. This paper uses a strong-tie/weak-tie framework to characterize the network structures of social media platforms (Granovetter 1973; Gibson 2001; Centola 2010; Valenzuela, Arriagada, and Scherman 2014). strong-tie and weak-tie networks differ in their ability to transmit social pressure. Therefore, each platform will have a different relationship with political participation (Valenzuela, Arriagada, and Scherman 2014). Platforms with strong-tie network structures, such as Facebook, can transmit social pressure across network ties. Participation in users on strong-tie platforms is more likely than participation on platforms with weak-tie network structures, such as Twitter.

Social media is composed of an interactive network of individuals, allowing researchers to examine the relationship between social factors and individual behavior. The literature has made progress in this area, moving beyond an individualistic cost and benefit calculation (Beck et al. 2002; Cho et al. 2009). This paper provides a necessary update to traditional collective action theory by incorporating social pressure as a psychological selective incentive into the utility function. The network structure of online social media platforms offers an opportunity to test the effects of collective interests and selective incentives on human behavior (Valenzuela, Arriagada, and Scherman 2014). Incorporating social concepts into collective action theory adjusts the payoffs associated with participation, allowing the strategy to become a rational decision within the model.

The Network Structure of Social Media Platforms

Social media platforms compete for users, offering unique options to differentiate themselves from other platforms. These choices influence the tie structure between individuals, allowing for variation in the way social media use influences behavior. The "strength of strong ties" and "strength of weak ties " hypotheses assist in characterizing these two network structures, guiding the assumptions of how each platform should impact protest participation.

Network structure describes the nature of the ties between individual actors within the network. These ties can either be “strong” or “weak” (Centola 2010; Valenzuela, Arriagada, and Scherman 2014). The strength of the tie is a combination of exposure, emotional intensity, intimacy, and reciprocity within the relationship (Granovetter 1973). The strong-tie hypothesis theorizes that strong social ties between individuals are necessary for networks to influence social behavior (Centola 2010). Homogeneous networks with deep linkages between group members will transfer and reinforce societal norms. According to this hypothesis, weak-tie networks are not able to transmit the complex concept of social pressure. Granovetter's “strength of weak ties” hypothesis posits that heterogeneous networks with weak social connections will better facilitate cooperation as information can extend over greater social distances (1973). Granovetter argues that small, homogeneous strong-tie networks limit the diversity and amount of information that individuals receive. Though some information may be available in strong-tie networks, this information is redundant as these networks are not efficient at spreading new information. Therefore, the effects of information alone will be weak in strong-tie networks.

Characteristics of social media platforms dictate whether the network structure is composed of weak or strong ties (Valenzuela, Arriagada, and Scherman 2014). While some social media platforms focus on transmitting information and fostering weak relations between individuals, others provide a network of strong social ties that will transmit social norms. This is not to say that a weak-tie network structure that primarily transmits information is unable to communicate social norms entirely, only that platforms based on strong ties send a more substantial number of social signals. The assumptions that follow each of these network structures allow researchers to use social media data to test for two possible causal mechanisms: 1) information transmission that facilitates coordination and enables participation and 2) social pressure as a selective incentive, stimulating participation.

This paper exploits the difference in the network structures of two social media platforms, Twitter and Facebook, to test impact of these causal mechanisms. Twitter is an example of a platform based on weak ties that specializes in *information transmission.* The focus is primarily to broadcast small pieces of information to many individuals. Twitter users are less likely to know the individuals in their network intimately. Twitter networks are heterogeneous: a user's network may consist of public figures, news organizations and other formal organizations in addition to regular users not in an individual's primary network. Facebook's network structure supports strong ties, enabling *social pressure transmission.* Individuals tend to connect with family, friends, and other members of their offline social network (Ellison, Steinfield, and Lampe 2007). Accounts are more often private with a focus on reciprocated ties versus spreading information publicly. Facebook's network structure supports the transmission of social information, allowing social pressure to play a role in an individual's decision-making process. Twitter use tests for the effect of information on participation, while Facebook use tests for the effects of social pressure.

A Theory of Social Pressure

This paper uses a collective action framework to explore *how* social pressure influences political participation. Free riding is a dominant strategy in the collective action literature, yet researchers observe individuals participating in high-cost endeavors. The inclusion of social pressure changes the utilities associated with strategies available to an individual. By incorporating this concept into the model, collective action theory can predict participation. Political participation becomes the dominant strategy instead of free riding.

The utility an individual derives from a particular action is composed of the benefits and costs associated with a contribution. The public good received from collective action, B, is a function of the number of actors contributing, k, which is always greater than the benefit received from only one contributor. C includes opportunity costs, the cost of obtaining skills, formally imposed sanctions, and information costs (Finkel and Muller 1998a). Information costs include gathering information regarding event logistics, the actors involved, and information on the public good (Abrams, Iversen, and Soskice 2011). To make this model easier to interpret, C is constant for all actors.[1] If $B>C$, then an individual will choose to contribute.

A collective action problem exists when either $(k)B < C$ or $B < C$ (Olson 1965; Ostrom 2000). The causal mechanism linking social media use and political participation depends on the nature of the collective action problem. The coordination problem occurs when the multiplied benefit of all actors contributing overcomes the cost of participation, but the benefit from a single actor contributing does not overcome the costs: $(k)B > C$, but $B<C$. "Conditional cooperators" are individuals who will participate as long as others will reciprocate (Ostrom 2000). If uncertain about the contribution of others, conditional cooperators will not contribute. If information on k is not available, a coordination problem exists. Here, the causal mechanism linking social media and political participation is social media's ability to lower transaction costs associated with coordination and information gathering.

A second collective action problem is the free rider problem. Free riding occurs when an individual, by relying on the contributions of others, receives the benefit of the collective endeavor without incurring the costs of participation. According to traditional rational choice theory, free riding is the dominant strategy. If free riding is the barrier to collective action, selective incentives are required to make participation a rational strategy (Opp 1986; Morton 1991; Uhlaner 1989; Klandermans 1984). Free riding is a ubiquitous issue in collective action; overcoming this problem often relies on

[1] Otherwise, C would vary on an individual basis to account for differences in education, social status, and different types of participation.

formal coordination through an organization, such as an interest group (Olson 1965). Organizations are able to provide selective incentives to encourage participation. Selective incentives are private, non-collective benefits offered in addition to the public good.

Selective incentives can be tangible as well as social and psychological (Olson 1965; Klandermans 1984; Ostrom 2000; Muller, Dietz, and Finkel 1991). In the model, *social pressure* is presented as a *psychological* selective incentive.[2] Individuals function as members of a social group and are heavily influenced by the norms of that group (Turner and Oakes 1986; Baumeister and Leary 1995). An individual's desire for social acceptance provides a strong incentive to follow group norms. Additionally, social exclusion serves as a strong deterrent to deviation from norms (Olson 1965). In groups where political participation is a valued norm, private goods such as social status and social acceptance are issued by the group to reward individual political participation. The addition of social pressure as a selective incentive changes the utility associated with participation: $u_i = (k)B + X - C$; X represents social pressure.[3] When $X > C$, participation can occur even if $(k)B < C$ or $B < C$, as the motivation lies in the X term.[4] Using this framework, the causal mechanism linking social media use and political participation is the transmission of social norms within the online network.

The social pressure term can take on a positive or negative value, reflecting both positive and negative instances of social pressure. This value is dependent on whether the term is used as a reward or as a deterrent, respectively. If positive, selective incentives are added to the payoffs associated with participating, $u_i = (k)B + X - C$. If negative, these incentives are deducted from the payoff associated with abstaining, $u_i = (k)B - X$. This is a departure from the traditional utility

[2] Psychological selective incentives solutions require that a party is willing to take on the cost of punishing deviations from the social norm; empirical evidence has found that these players do exist. "Willing punishers" will apply sanctions to those who do not engage in collective action (Ostrom 2000).

[3] This approach stems from Oliver's model of incorporating selective incentives into the payoff structure (1980). Terms have been modified for simplicity, though they remain theoretically equivalent.

[4] Selective incentives may not be able to overcome costs in all instances. For example, during extremely violent actions, the high cost of participation cannot be overcome to make participation a rational strategy – even for typical conditional cooperators.

associated with abstaining, $u_i = (k)B$, where no consequences are incorporated. X is held constant to represent the dichotomous explanatory variable used in the model. Realistically, X will vary between individuals depending on their exposure to social pressure and the type of collective action in question. Figures 1 and 2 present the utilities associated with protest participation with and without the provision of selective incentives. Table 1 shows the preference over outcomes for Actor A, who is not exposed to selective incentives, and Actor B, who receives selective incentives. When selective incentives are introduced, the highest utility is associated with participation. Without selective incentives, the highest utility is associated with free riding. The addition of selective incentives to the payoff matrix allows participation to become a rational choice for individuals who would otherwise free ride.

The theory of social pressure is concerned with the transmission of *social norms* along ties between individual actors within a network. These norms function as psychological selective incentives in the model, encouraging socially acceptable behavioral outcomes. Information received via social ties provides knowledge regarding the social rewards available for abiding by norms ("positive" social pressure) and the social sanctions associated with divergence ("negative" social pressure). Public or private messages that promote political participation are distributed via the social media platform. These messages are considered instances of social pressure. Positive social pressure comprises of calls to action, stressing one's duty as a member of society to assist in achieving the public good. Negative social pressure includes describing free riders as hypocrites or traitors to the cause, which would compromise the free rider's social standing.

I theorize that social media platforms with strong-tie network structures have a greater impact on protest participation due to their ability to transmit social pressure. Weak-tie platforms primarily transmit information, which only increases participation when the barrier to collective action is the coordination problem. Strong-tie networks are able to stimulate free riders by providing social pressure as a selective incentive. The addition of selective incentives into this equation allows free riders to participate by increasing the payoffs associated with participation, making it a rational strategy.

Figure 1: Collective Action Model 1: No Selective Incentives

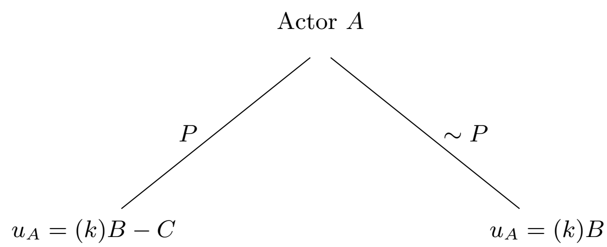


Figure 2: Collective Action Model 2: With Selective Incentives

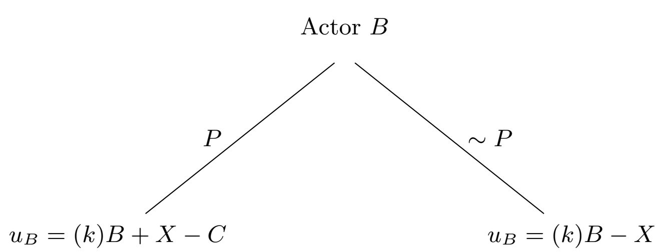


Table 1: Change in a Free Rider's Preference Ordering with the Addition of Selective Incentives

Preference Ordering:	1	2
Actor A (No Select Incentives)	$(k)B$ (Free ride)	$(k)B - C$ (Participate)
Actor B (With Select Incentives)	$(k)B + X - C$ (Participate)	$(k)B - X$ (Free ride)

Collective Interest vs. Selective Incentive Approaches

There is mixed evidence as to which causal mechanism better explains participation, access to information or psychological selective incentives. Theoretical predictions and empirical realities in explaining collective action situations often differ. Theoretical predictions find that rational individuals will not contribute, while empirical evidence shows that many individuals engage in some form of participation. The integration of behavioral concepts into theoretical models is essential for developing a theory of collective action that correctly predicts human behavior.

Two main approaches are used to explain why individuals choose to participate in a protest, the *collective interest* model, based on access to information, and *selective incentive* models, which account for social influence (Finkel, Muller, and Opp 1989; Muller, Dietz, and Finkel 1991; Finkel and Muller 1998a). According to the collective interest model, an individual will participate if three criteria are met: 1) They are not content with the current public goods provision, 2) they believe that through collective effort, the group will be successful in providing the public good, 3) they believe that their individual contribution will improve the chances of achieving the public good. The collective interest approach focuses on "collective rationality"; individuals will participate if the chances of group success are reasonably high (Finkel, Muller, and Opp 1989). Achieving these goals requires coordination and access to information.

Research has found support for social pressure as a predictor of voting behavior, serving as a solution to the paradox of voting (Gerber and Green 2000; Abrams, Iversen, and Soskice 2011). The literature on political protest suggests that social/psychological selective incentives do play a role in behavior outcomes (Klandermans 1984; Muller, Dietz, and Finkel 1991). Proponents of the collective interest model find that selective incentives are often a weaker predictor compared to information-based variables (Finkel and Muller 1998a; Lichbach 1994). I argue that weak support for social pressure theory results from the difficulty in measuring social pressure, specifically in regards to response bias. Group norms are deeply ingrained in individuals, making social pressure a difficult concept to express and isolate within a survey. Studying psychological variables is difficult as researchers must rely on recollections of past behavior. Recollections are influenced by an individual's current psychological state, including the expectations of their social group (Finkel and Muller 1998a). Selective incentives produce behavior in free riders that is identical to that of conditional cooperators. Researchers may be measuring the effects of social pressure within the variables typically attributed to collective interest variables: social norms may color the level of satisfaction with current public goods, the perceived likelihood of a political movement's success, or the response to information regarding the protest. At the very least, social pressure may mitigate the relationship between the collective interest variables and protest participation. Protest literature also points out the difficulty with establishing causality regarding social influence: responses to survey questions regarding social pressure may be used by individuals to rationalize their behavior after the fact (Finkel and Muller 1998a). Therefore, it is difficult to determine whether attitudes and social influence affect participation or whether participation influences attitudes and perceptions of social influence.

This study is designed to circumvent the issues with measuring social pressure by analyzing an individual's interaction with a social media network, which serves as a proxy for social pressure. The respondent's exposure to social pressure is estimated by using assumptions regarding the network structure of that platform. Facebook users will receive social pressure through the platform's strong-tie network. Twitter users, on the other hand, are part of a weak-tie network whose network structure is only conducive to information transfers. The respondent is not required to reflect on subjective topics such as social pressure the answers received are less vulnerable to response bias.

Researchers are presented with new opportunities to study the mechanisms that drive individual participation in collective endeavors as political participation evolves. Through analyzing online social networks where communication is transparent, researchers can measure social interaction with greater ease, including both content and frequency of interaction. Investigating the network structures of social media platforms offers an opportunity to compare different environmental factors that contribute to political participation. Facebook's strong-tie network structure allows us to target the effects of the social environment, which contains information on social norms and group values. If the selective incentive model is a better predictor of participation, collective action should occur within online networks that can transmit social selective incentives.[5] Using Twitter's weak-tie network, we can target the effects of another context important in collective action models: the information environment. If the collective interest model is a better predictor of participation, we should see higher rates of participation in networks that effectively transmit information.

Data

Analyzing both Facebook and Twitter use tests which mechanism produces higher rates of protest participation: the application of selective incentives through Facebook's strong-tie network structure *or* an increase in access to information via Twitter's weak-tie network structure. The dataset used in this paper comes from the Tahrir Data Project.[6] The project initially surveyed 1,200 average participants in the 2011 Egyptian Revolution, offering 1,037 usable observations. Popularly referred to as the January 25th protests, this revolution was part of the Arab Spring, a response to decades of governmental abuse and corruption in the region (Beinin 2012). The movement included numerous strikes and demonstrations. Information sharing through social media platforms was present prior to and during the protests (Beinin and Vairel 2011). Protest efforts lasted throughout 2011 and continued into early 2012, eventually ousting President Mubarak. This dataset contains information

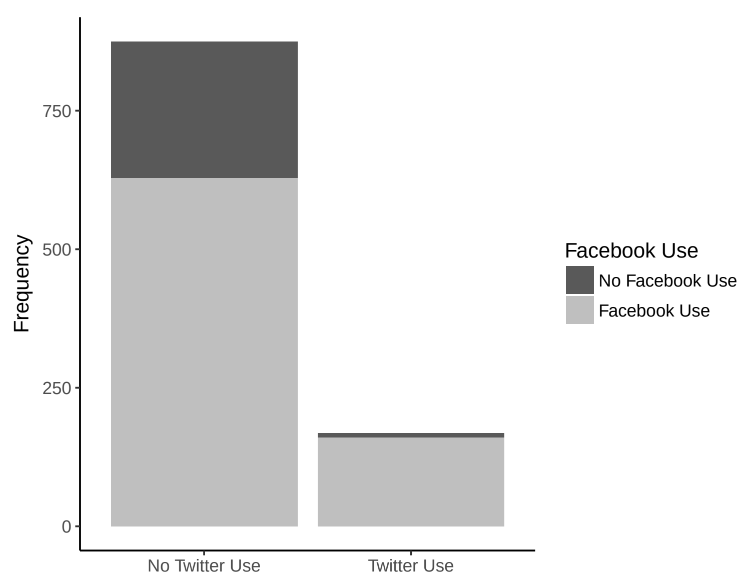
[5]The model does not assume Facebook cannot transmit non-social information, only that the strong-tie network structure is more efficient at transmitting social norms than information (Granovetter 1973; Centola 2010).

[6]The dataset is available at: https://www.theengineroom.org/projects/tds/.

on media use in Cairo from January 2011 to February 2011. The survey targets the individual protester's formal media use, face-to-face interactions, and internet and social media use during the January 25th protests.

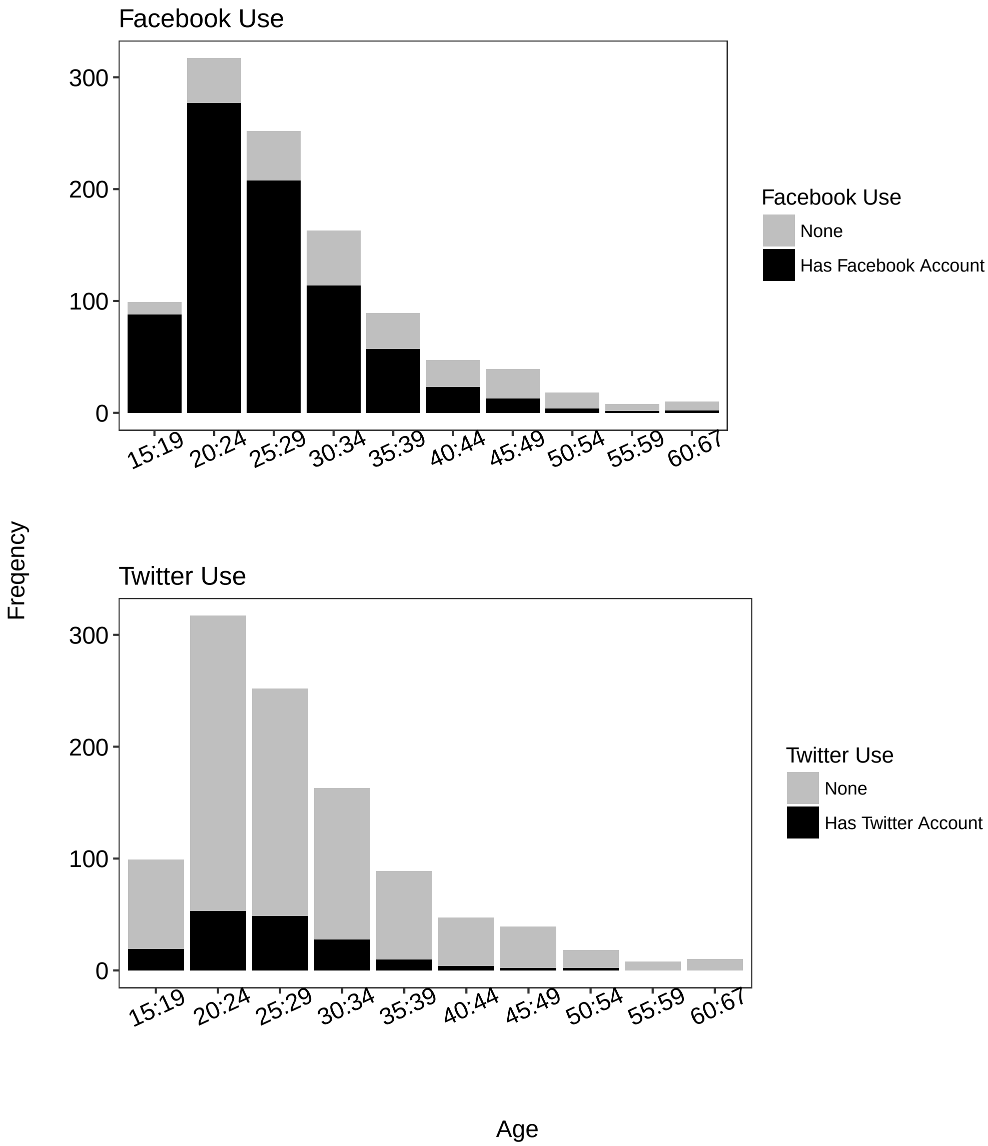
Figure 3 displays social media use among participants, including how many participants used one, both, or neither social media platform. It is important to note that only 16% of the participants were Twitter users, while 75% of participants had a Facebook account. Out of all participants, 23% of users had neither a Facebook nor a Twitter account, while 15% had both. 60% had only a Facebook account, but less than 1% of individuals had only a Twitter account. These numbers are reflective of worldwide social media use at the time: Pew reported that around 58% of the adult population had a Facebook account, while only 19% reported using Twitter in 2014 (Duggan et al. 2015).

Figure 3: Facebook vs. Twitter Use during the 2011 Egyptian Revolution



Seventy percent of protesters in the sample were between 20 and 34 years old. This age range also carried the greatest number of social media users: 76% of all Facebook users and 78% of all Twitter users were between 20 and 34 years of age (see Figure 4). In the sample, social media

Figure 4: Facebook and Twitter Use by Age During the 2011 Egyptian Revolution



Note: Facebook and Twitter use are dichotomous values.

use declined as age increased. This relationship is not unexpected: younger individuals tend to use the internet and social media at higher rates (Mossberger 2008; Margetts et al. 2015). Table 2 provides information on engagement in other activities and forms of media use by the individuals in the sample. Thirty-five percent of individuals participated in previous protests, and 34% of individuals belonged to formal organizations. Over 90% of participants watched satellite television, used telephone services, and had face-to-face contact with others during the protests. Over half of the participants used text messaging (SMS), read print newspapers, and used email during the demonstrations. Only 8.9% of the sample used blogs. 31% relied on radio news during the protests.

Table 2: Engagement in Other Forms of Participation/Mediums

Variable	**Percentage of Sample**
Previous Protest Participation	35 %
Previous Organization Membership	34 %
Face-to-Face Contact	93 %
Phone Use	92 %
TV	94 %
Radio	31 %
Newspaper	66 %
E-mail	59 %
Blog Use	9 %
SMS Use	66 %

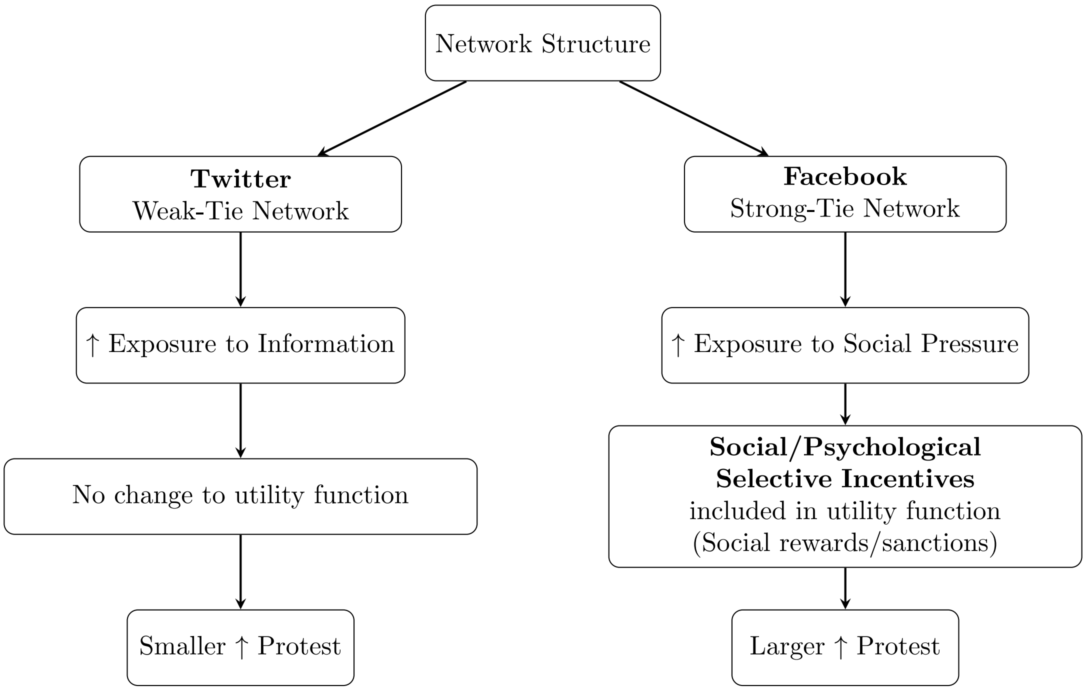
A random sample was not available, as many individuals were fearful of talking to reporters and researchers. A snowball sampling technique aided in recruiting Cairo protesters: willing individuals recommended others who they thought would also participate in the survey. Snowball approaches allow researchers to access "hidden populations" where there is no sampling frame and where research would otherwise be impossible (Heckathorn 2002). A drawback to non-probability sampling methods is the potential to introduce bias into the sample, making statistical inference unavailable. Despite these concerns, statistically-valid estimators can be derived from respondent-driven sampling techniques: in large enough samples, biases from the selection process become weaker and eventually negligible (Heckathorn 2002).

The benefit term of the collective endeavor is held constant by limiting the data to a single protest. In this case, the public good is the overthrow of the Mubarak regime. This technique also holds constant the cost of participation: the risk of arrest and threats to personal safety was consistent among the Tahrir Square protesters. The January 25th demonstrations were a high-cost, high-benefit endeavor. Therefore, an initial bias in strategies should not exist. A high-benefit, low-cost protest may bias the results towards participation, while a low-benefit, high-cost protest would result in lower rates of participation. During the Egyptian revolution, there were likely to be both conditional cooperators pursuing the benefit of ousting the Mubarak regime as well as free riders seeking to avoid the high costs of participation. Restricting the data to a single protest and geographic location also offers control for the general direction of social norms occurring within the social network. Different cultures take a variety of stances in response to civil disobedience. Limiting the social norms present avoids confusion from contradicting norms, which is necessary to determine how network ties influence participation. In the Egyptian context, psychological selective incentives received by individuals should encourage protest participation, not stifle it.

Theory & Hypothesis

Using a collective action framework, I theorize that the presence of social pressure within an individual's social network affects the likelihood that he or she will engage in protest. Social pressure functions as a psychological selective incentive, motivating participation when free riding is the barrier to collective action. Social pressure is an additive measure that provides an incentive to participate beyond the benefit term alone. Social media platforms with a strong-tie network structure will transmit social pressure. Social media platforms with a weak-tie network structure are efficient at spreading political information, but are not able to transmit social pressure. Comparing Facebook (strong-tie network structure) and Twitter (weak-tie network structure) explains *why* social media use impacts political participation through examining two causal mechanisms: social pressure and information, respectively. These relationships are illustrated in Figure 5.

Figure 5: Theory



H1: Social Pressure Hypothesis

An increase in Facebook use leads to an increase in the number of acts of participation committed by an individual protester.

Facebook users will receive social pressure to participate in collective action through the platform's strong-tie network structure. Social pressure increases the payoff associated with participation while decreasing the payoff associated with abstaining, making this strategy a rational choice. Increased exposure to social pressure increases the likelihood that an individual will engage in protest. Increased exposure influences both 1) individuals who would otherwise choose to free ride and 2) conditional coordinators. Conditional coordinators are already highly likely to participate due to the benefit term; social pressure further increases the payoffs associated with participating.

H2: Information Hypothesis

An increase in Twitter use leads to an increase in the number of acts of participation committed by an individual protester.

Twitter users will have access to more information regarding a collective endeavor due to the flow of information within a weak-tie network. Conditional coordinators require knowledge of others' participation to engage in collective action. Twitter fulfills this requirement and facilitates participation among conditional coordinators.

H3: Selective Incentives vs. Collective Interest Hypothesis

Facebook use has a greater impact on the number of acts of participation committed by an individual than Twitter use.

Twitter use increases participation for conditional coordinators only. Free riders are not influenced by information alone: the highest payoff is associated with abstaining in the absence of social pressure. Facebook use increases participation for free riders *and* conditional coordinators through exposure to social pressure. A higher overall impact on the number of acts of participation is expected from Facebook compared to Twitter use.

Using social media data and the assumptions of the network structures allows us to theoretically differentiate selective incentives and collective interest variables as causal mechanisms. To accomplish this statistically requires the use of an interaction term, which will remove any influence of the psychological selective interest variable (Facebook) on the collective interest measure (Twitter). When one constituent term's value is equal to zero, the independent effect of the second constituent term is visible. This technique avoids attributing any of the effects of psychological selective incentives to collective interest variables, an issue faced by prior researchers who found a weak relationship between selective incentives and protest participation.

H4: Interaction Hypothesis

Facebook use increases the impact of Twitter use on the number of acts of participation committed by an individual.

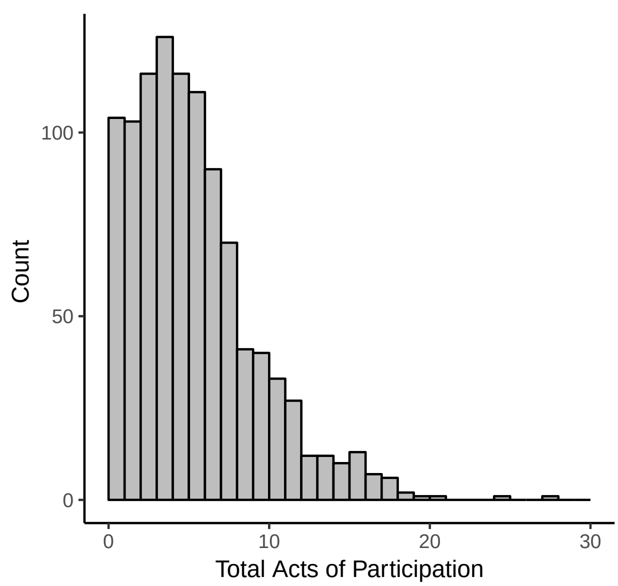
It is unlikely that social pressure and information work in complete isolation from each other, as they are both used to determine the payoff associated with a particular strategy (i.e., $u_i = (k)B + X - C$). Social pressure mitigates the effect that collective interest variables have on participation. The level of information in their network influences individuals, but this is dependent on the amount of social pressure received. Individuals who receive social pressure and can easily access information are more likely to participate than individuals who receive social pressure but lack access to information. Once social pressure is applied through Facebook's network, Twitter use can increase the participation of the former free riders by providing access to information regarding the protest.

Measures & Model Estimation

Constructing the Dependent Variable

For the dependent variable, a separate measure of protest participation is required as the dependent variable as all of the respondents in the Tahrir Dataset were protesters during the January 25th demonstrations. This measure is achieved by aggregating the number of times that an individual used an "outlet" to share information regarding the protests with others. During the survey, the respondent reported if they had received information from ten sources: phone conversations with others, SMS communication, Twitter use, Facebook use, reading blogs or printed news, watching satellite TV, listening to the radio, email, and through in-person communication. All of these exchanges occurred *during* the protests. For each of the ten possible sources of information, the individual reported if they *shared* that information through any outlets, which included in-person conversation, text messages, or via the Internet. Internet communication includes social media posts and messages, blog posts, and emails. If the respondent did not share information via these outlets, the response was coded as "0" for each outlet. If the respondent did share information via conversation, SMS, or the internet, the received a score of "1" for each outlet they used. Each report of information sharing (score = "1") was considered an "act of participation". These reports are aggregated to create the total number of acts of participation (information sharing) per individual, Y_{Acts}.[7] The distribution of participation is displayed in Figure 6. The majority of respondents participated by sharing information between one and 12 times, with a mean score of 5.8 acts of participation. Thirty-one individuals did not participate by sharing information according to this measure. The highest score in the sample was 28 acts.[8]

Figure 6: Distribution of Dependent Variable Y_{Acts} (Total Acts of Participation)



[7] Figure 42 in Appendix 1 provides the survey questions used and the aggregation strategy in constructing the dependent variable. For example, an individual responded if they had *received* information regarding the protest through *text messages*. If yes, a follow-up question asked "Did you share what you learned in *text messages* through 1) conversation, 2) text messaging, or 3) the Internet." Some sources had additional categories, such as "re-tweeting" or "other" (see Figure 42, Appendix 1). The respondent could respond "yes" or "no" to each option listed. Each "yes" response to sharing information was coded as "1," counting as one act of participation.

[8] The highest achievable score in the survey was 40 acts of participation.

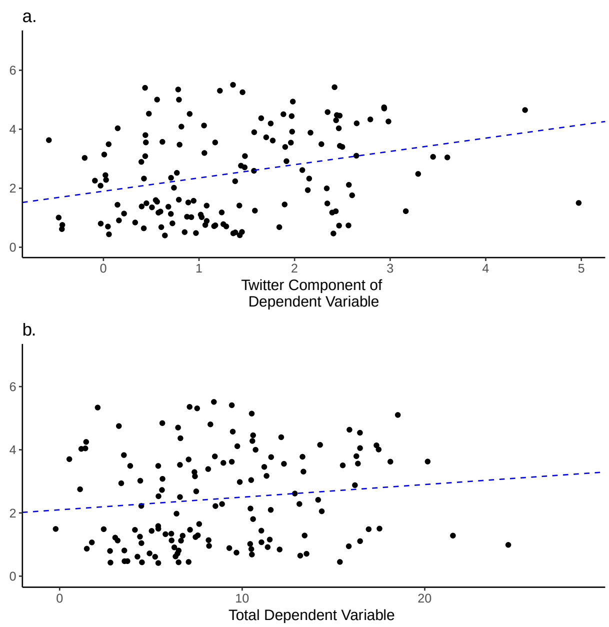
Validating the Dependent Variable Measure

The survey questions provide a dichotomous response as to whether the individual shared information via that medium, but lacks details on how *intensely* the individual shared information. Those who shared to multiple outlets are *assumed* to be "intense participators". However, the dichotomous response does not allow differentiation between an individual who received information through Facebook and shared information once, and a person who shared information 100 times. The degree of participation by information sharing for nine out of the 10 available sources within this survey is not directly measurable; Twitter is the only source that provides a comparison between the intensity of use and the dichotomous measure capturing information sharing used in constructing the dependent variable, Y_{Acts}. A survey question regarding the intensity of Twitter use tests this assumption: "*How many times* did you send information about the protests on Twitter?" The respondent can select from five categories, ranging from "0-20" to "More than 1,000.' This measure of intensity was compared to the measure of information sharing through Twitter used in constructing the dependent variable: did the respondent share what they had learned on Twitter through 1) conversation, 2) text messaging, 3) the Internet, 4) re-tweeting, or 5) "other," receiving a maximum score of five shares/acts. The Twitter intensity variable has a positive and significant linear relationship with the Twitter information sharing variable.[9] The correlation is displayed graphically in Figure 7(a) Respondents who reported that they shared information intensely via Twitter (y-axis) also tended to be individuals with higher scores for the component of the dependent variable measuring Twitter-based acts of participation only (x-axis). These findings suggest that the information sharing variables used to construct the dependent variable, Y_{Acts}, are reliable proxies for participation. The Twitter intensity variable was also positively related to the fully aggregated dependent variable, Y_{Acts}, see Figure 7(b). This relationship is not statistically significant,

[9]OLS Regression Coefficient = .43, $p<0.05$.

which is not expected as the intensity of Twitter use may not correspond in a meaningful way when compared to information sharing from other sources, such as radio or satellite TV.

Figure 7: Correlation between Twitter Intensity Measure and Dependent Variable



Note: in Figure 7(a), the survey question for the y-axis is "How many times did you send information about the protests on Twitter?" For the x-axis: "Did you share what you learned on Twitter through conversation, text messaging, or the Internet (select all apply)?". In Figure 7(b), the y-axis remains the same, while the x-axis represents the sum of all source questions.

Model Estimation

The model's main independent variables, *Twitter Use* and *Facebook Use* measure the frequency of Twitter or Facebook during the Jan 25th protests.[10] The two variables have three categories each regarding the respondents use of that platform, "No," "Occasionally," and "Regularly." Survey questions are provided in Appendix 1. The model includes an interaction term, *Twitter Use *Facebook Use*. Including this product term offers two advantages. First, the effect of both of these variables working together is captured simultaneously. This method tests the interaction hypothe-

[10] Statistical model:

$$\begin{aligned} Y_{Acts} = \beta_0 + \beta_F FacebookUse + \beta_T TwitterUse + \beta_{TF} Facebook * TwitterUse \\ + \beta_O PriorOrganization + \beta_P PriorProtest + \beta_S Sources + \varepsilon_i + \beta_C Controls + \varepsilon_i, \end{aligned} \tag{1}$$

sis, that $Facebook\ Use$ increases the impact of $Twitter\ Use$ on the acts of participation committed by an individual (Y_{Acts}). The marginal effect of $Twitter\ Use$ on participation is a function of both the Twitter and Facebook variables.[11] Second, users may have both media sources, making effects difficult to distinguish. Providing a product term removes interactive information from the constituent terms to display the effect of X on Y when $Z = 0$. This effect is theoretically interesting as it confirms that social pressure has a separate and unique effect from the influence of information.

Prior Organization Membership captures an individual's engagement with an organization prior to the protests, including unions, political parties, and charities. *Prior Protest Participation* measures if an individual participated in a movement prior to the Jan 25th protests. Prior civic engagement is shown to increase the likelihood that an individual will engage in future opportunities (Finkel, Muller, and Opp 1989). These individuals may be more inclined to use Facebook or Twitter during the protests as a tool to spread information. In this case, participation is a result of prior experience, not a result of influence from the individual's online networks. These two variables control for prior experience with political participation that may influence Facebook and Twitter's relationship with the dependent variable.

The impact of outside sources of socially based influence on Facebook or Twitter's role in the model is controlled by including independent variables for phone conversations, in-person conversations, SMS, and blogging. An individual's offline social network may encourage individuals to use social media sources, reducing communication costs for the entire group. This paper is only concerned with the effects of social pressure stemming from social media use. For other sources of influence, the network structure and tie strength between individuals who engage in phone conversation, in-person conversations, SMS and blogging cannot be assumed. Control variables are included

[11] The marginal effect of $Twitter\ Use$ on the acts of participation, conditional on $Facebook\ Use$:

$$\frac{\partial E(Y Acts)}{\partial Twitter Use} = \beta_{Twitter Use} + \beta_{Facebook*Twitter} Facebook$$

for the respondent's age, gender, level of education, and the respondent's reported neighborhood of residence within Cairo. Incorporating the neighborhood variable allows for more control of possible differences in social norms that may exist among residents of Cairo.

Results

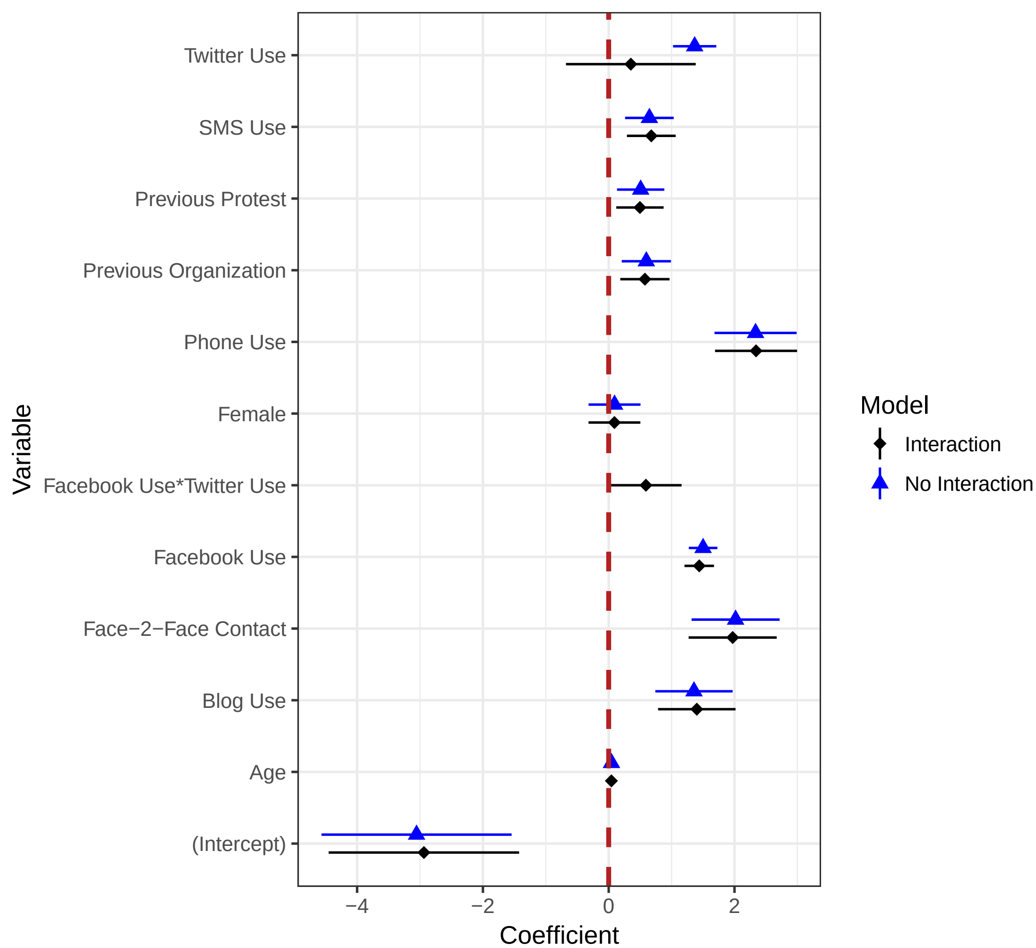
This paper investigates the network structures of two social media platforms to determine which causal mechanism has a greater impact on individual behavior: social pressure as a psychological selective incentive or traditional collective interest/information based approaches. These causal mechanisms are tested using the assumptions of strong-tie and weak-tie network structures. Strong-tie networks are able to transfer social pressure between individuals and are a characteristic of Facebook networks. Twitter networks share the characteristics of weak-tie networks that are efficient at transferring information, but not social pressure. The results of the OLS regression models are shown in Figure 8. A complete table and robust regression estimates are provided in the Appendix 2, see Tables 6 and 7.[12] Figure 8 presents the results of a non-interactive model, Model 1, and an interactive model, Model 2. Comparing these models captures the difference in output among all variables when accounting for the interaction occurring between the information variable, Twitter, and the social pressure variable, Facebook. For context, an increase by a single act of participation represents a 3.5% change in participation.[13] In non-interactive Model 1, both the use of Twitter and Facebook have a positive, significant relationship with the number of acts of participation committed. As $FacebookUse$ increases, participation increases by 1.5 acts, a 5.4% increase. As $TwitterUse$ increases, participation increases by 1.4 acts, a 5% increase. This provides support for both the Social Pressure Hypothesis, that an increase in $FacebookUse$ leads to an increase in

[12] Robust regression is used to account for heteroskedasticity in the sample.

[13] To determine the percentage change, one unit is divided by the highest number of acts committed in the sample, 28 acts (1/28=3.5). A one unit change in participation taken over all possible opportunities in the survey, 40 acts, would represent a 2.5% change.

the number of acts of participation, and the Information Hypothesis, that increase in $TwitterUse$ leads to an increase in the number of acts of participation. When using a non-interactive model, both of these variables present as important contributors to the outcome of participation. However, these estimates are not significantly *different* from each other; there is no support for the Selective Incentives vs. Collective Interest Comparison Hypothesis, that $FacebookUse$ has a greater impact on the number of acts of participation committed by an individual than $TwitterUse$.

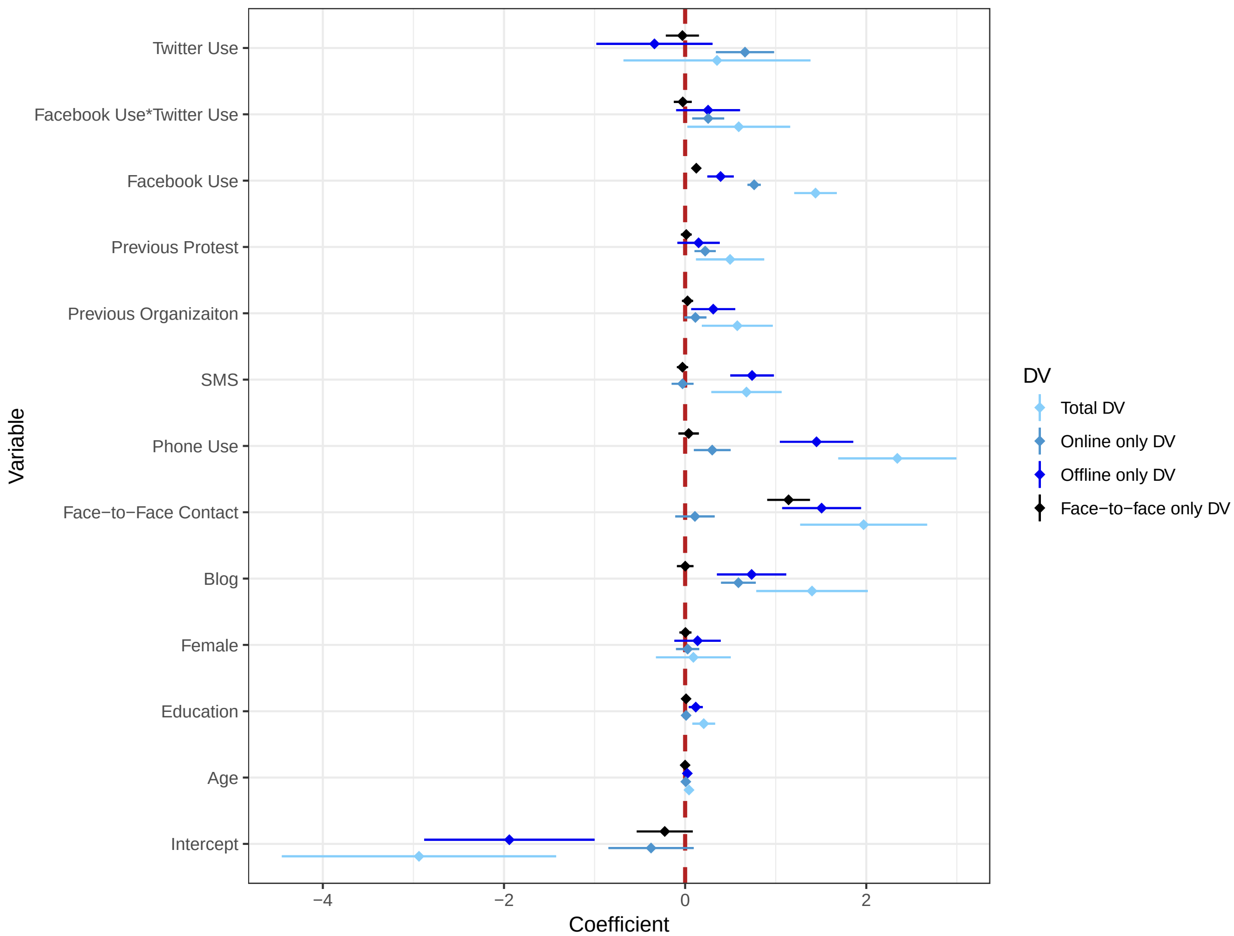
Figure 8: OLS Regression Results: A Comparison of Interactive and Non-Interactive Linear Models



Data Source: Tahrir Data Project. Points are OLS regression coefficients, with 90% confidence intervals. A full table of regression estimates is available in Table 6, see Appendix 2.

In Model 2, a product term is included to capture the interactive effect occurring between social pressure and information as causal mechanisms. This model offers a more accurate test of the

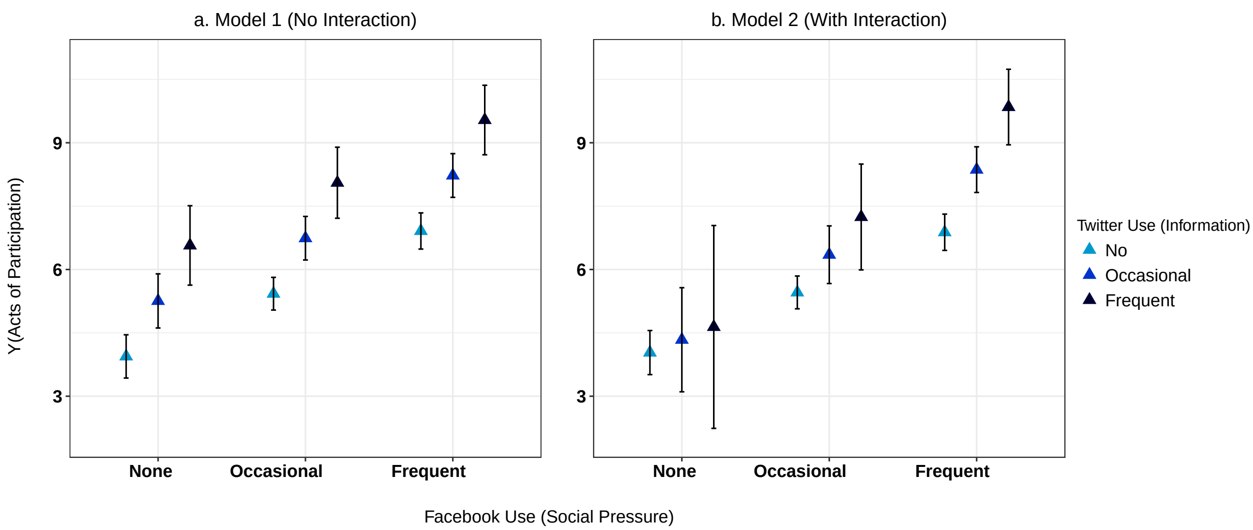
Figure 9: OLS Regression Results: The Effect of Social Media Network on Online, Offline, and Face-to-Face Acts of Participation



Note: predicted values are derived from OLS regression estimates with standard error bars. A full table of regression estimates is available in Table 8, see Appendix 2.

Selective Incentives vs. Collective Interest Comparison Hypothesis: it determines the influence of both variables when the opposing variable is equal to zero, removing any interactive effects from the constituent terms that may influence the findings. When the product term is included in Model 2, $FacebookUse$ remains positive and significant, increasing participation by 1.4 acts (5%) when $TwitterUse$ is equal to zero. This finding provides support for the Social Pressure Hypothesis. In Model 2, the Twitter variable fails to reject the null hypothesis when $FacebookUse$ is held at zero. This is likely an artifact of the data: there are few users who only have Twitter accounts and, therefore, independent effects are hard to clarify. Theoretically, this result is feasible: cases where an individual does not receive some form of social influence are likely to be very small, if not nonexistent. Using a product term enables a test of the Interaction Hypothesis, that $FacebookUse$ increases the impact of $TwitterUse$ on the number of acts of participation committed by an individual. The interaction term is significant and positive, providing support for the Interaction Hypothesis. The effect of these variables occurring together increases participation by 0.59 acts, which is a 2.1% increase in total acts of participation committed by an individual.

Figure 10: Predicted Values: Acts of Participation Given the Level of Twitter Use



Note: predicted values are derived from OLS regression estimates with standard error bars. A full table of regression estimates is available in Table 6, see Appendix 2.

To test if $FacebookUse$ and $TwitterUse$ have different effects on information sharing generated from online versus offline sources, Model 2 is applied to three configurations of the dependent variable. If social media use is only able to influence information sharing of information generated within online sources, social media use is considered to have less of an impact on behavior as it is only able to alter online behavior. Additionally, information gathered and distributed via online channels is low cost; individuals are engaging in only low-cost forms of participation. However, if individuals are willing to take on the additional cost to transmit information received in offline environments, such as through the newspaper or radio, social media use is considered to have a much stronger effect. These efforts are more costly: it takes more effort both to receive and distribute offline information. This outcome has real-world consequences concerning the diversity of information available. It would show that a variety of information sources are still present even if social pressure occurs in *online networks*. Figure 9 displays these results. The three variations of $Y(Acts)$ are limited to the source of information: online sources, offline sources or face-to-face sources only.[14] $FacebookUse$ has a positive, significant effect on all variations of the dependent variable, whether $Y(Acts)$ was based on information from an online, offline, or even a face-to-face source. Social pressure received from $FacebookUse$ supports diversity in information, as the information they shared is obtained from a variety of sources. $TwitterUse$ only had a positive, significant effect when $Y(Acts)$ was based on information from an online source. This finding indicates that influenced within a weak-tie network structure is only able to aide in the flow of information generated online. It does not encourage the sharing of information from offline or face-to-face resources. This is reflected in the interaction variable, $FacebookUse * TwitterUse$; $FacebookUse$ is able to increase the impact of $TwitterUse$ on $Y(Acts)$ for the Online only $Y(Acts)$. Despite the impact of $FacebookUse$, $TwitterUse$ is still not able to have a significant impact on $Y(Acts)$ for offline and face-to-face configurations of the dependent variable.

Figure 10 shows the predicted values of $Y(Acts)$ across different levels of $FacebookUse$ and $TwitterUse$ for both the non-interactive model, Model 1, and the model with the interaction term included, Model 2. Both Figure 10(a) and 10(b) plot predicted outcomes for the three levels of $TwitterUse$ over the three levels of $FacebookUse$. In Figure 10(a) using Model 1, for all levels of

[14]Offline sources include 1) phone 2) TV 3) Radio 4) Newspapers. The survey questions are: "Did you share what you learned through phone conversations/ TV/ the Radio/ Newspapers through conversation, text messaging, or the Internet (select all apply)?". Online sources include 1) Twitter 2) Facebook 3) Blogs 4) Email, the survey questions are: "Did you share what you learned through Twitter/ Facebook/ Blogs/ Email through conversation, text messaging, or the Internet (select all apply)?" The Face-to-face source includes only information obtained through live conversation: "Did you share what you learned through live conversation through conversation, text messaging, or the Internet (select all apply)?"

$FacebookUse$ there is a statistically significant difference between *No* $TwitterUse$ and *Occasional* $TwitterUse$, and between *No* $TwitterUse$ and *Frequent* $TwitterUse$.[15] When the interaction is included in Figure 10(b) using Model 2, no difference is found between the levels of $TwitterUse$ when $FacebookUse$ = *No*.[16] The large standard error associated with *Frequent* $TwitterUse$ and $FacebookUse$ = *No* is due to the lack of observations in the data that fit both of these categories. This also corresponds with theoretical assumptions: due to human nature, it is unlikely that an individual will not interact with a social group, yet will manage to expose themselves to formal information sources. In Figure 10(b) using Model 2, as $TwitterUse$ increases, a greater change between these values occurs within *Frequent* $FacebookUse$ values than within the *No* $FacebookUse$ category.[17] When $FacebookUse = 0$, Y increases by just 0.6 acts from *No* $TwitterUse$ to *Frequent* $TwitterUse$. When Facebook= *Frequent*, Y increases by 2.6 acts between *No* $TwitterUse$ and *Frequent* $TwitterUse$; additionally, the two values are significantly different.[18] These patterns are not seen in the predicted values in Figure 10(a) using Model 1: when the interaction is not accounted for, change appears consistent across all three categories of $FacebookUse$. With *Frequent* $FacebookUse$, a statistically significant difference is found between the predicted outcome for individuals with *No* $TwitterUse$ (6.9 acts of participation), *Occasional* $TwitterUse$ use (8.4 acts) and *Frequent* $TwitterUse$ use (9.8 acts). These values display a slight increase from the predicted values at the same levels of $TwitterUse$ and $FacebookUse$ in Model 1.[19] While the differences in $TwitterUse$ values between models is small when $FacebookUse$ = *Frequent*, the estimates produced in Model 2 are *significantly different* from each other: The three Twitter values produced by Model

[15] No significant difference is found between *Occasional* $TwitterUse$ and *Frequent* $TwitterUse$ in Model 1.

[16] In Figure 10(a) using Model 1, the predicted outcome for *Frequent* $TwitterUse$ and *No* $FacebookUse$ is 6.56 acts of participation and is significantly different from *No* $TwitterUse$. In Figure 10(b) using Model 2, the predicted outcome for *Frequent* $TwitterUse$ drops to 4.6 acts when $FacebookUse = 0$ and is not significantly different from *No* $TwitterUse$.

[17] This relationship is clarified in Figure 43 in Appendix 2. Identical information is presented and the data is displayed using the level of $TwitterUse$ on the x-axis.

[18] When $FacebookUse = Occasional$, $TwitterUse$= *Frequent* is different from $TwitterUse$= $None$, however this effect drops to 7.2 Acts; in In Figure 10(a) using Model 1 this value was 8.1 Acts.

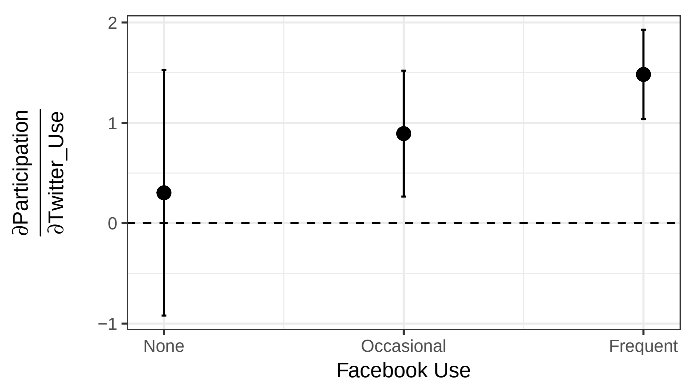
[19] 6.9 acts for *No* $TwitterUse$, 8.2 acts for *Occasional* use, and 9.5 acts for *Frequent* use.

1 are not significantly different for *Frequent* $FacebookUse$.

These findings provide support for both the Social Pressure Hypothesis and the Information Hypothesis. As both values of $FacebookUse$ and $TwitterUse$ increase, we observe higher values of $Y(Acts)$. The findings in Figure 10(b) also support the Selective Incentives vs. Collective Interest Hypothesis, that Facebook use has a greater impact on the number of acts of participation committed by an individual than Twitter use. The value $Y(Acts)$ when $FacebookUse = Frequent$ and $TwitterUse = 0$ is 6.9, while the value $Y(Acts)$ when of $TwitterUse = Frequent$ and $FacebookUse$ $= 0$ is only 4.6 Acts. $FacebookUse$ increases $Y(Acts)$ by 2.3 acts compared to $TwitterUse$.

The interaction term, $FacebookUse * TwitterUse$ is positive and significant, providing preliminary evidence for the Interaction Hypothesis: $FacebookUse$ increases the impact of $TwitterUse$ on the number of acts of participation committed by an individual. Figure 11 displays the marginal effect of $FacebookUse$ on the relationship between Twitter and the number of acts of participation committed by a respondent. Marginal effects provide coefficient estimates of one variable in the two-way interaction, conditional on the value of the second variable. The plot shows that by increasing $FacebookUse$ (x-axis), the magnitude of the coefficient of $TwitterUse$ on Y_{Acts} also increases (y-axis). $TwitterUse$ alone does not have a significant impact on Y_{Acts} when $FacebookUse$ $= 0$. The values begin to become substantively and statistically significant with Occasional or Frequent $FacebookUse$. The impact of Twitter on participation increases to .89 acts with *Occasional* $FacebookUse$ (+3.2%). With *Frequent* $FacebookUse$, Twitter increases participation by 1.48 acts (+5.3%). This finding provides further support for the Interaction Hypothesis. I theorize that the direction of influence flows from the social pressure variable to the information variable; social pressure mitigates the effect that information availability will have on individual participation. This is evident in the data; $TwitterUse$ has a null direct effect in the interactive model compared to the statistically significant impact of $FacebookUse$ on the dependent variable.[20] The rationale of theorizing that influence flows from $FacebookUse$ to $TwitterUse$ is further supported by Figure 12, displaying the marginal effect of $TwitterUse$ on the relationship between $FacebookUse$ and Y_{Acts}. When $TwitterUse = 0$, the effect of $FacebookUse$ on Y_{Acts} is positive and significant, with a coefficient of 1.42 acts of participation. The marginal effect of $FacebookUse$ on Y_{Acts} is not dependent on $TwitterUse$ to sustain a significant impact on the dependent variable. The effect of $FacebookUse$ on Y_{Acts} is statistically significant at all levels of $TwitterUse$. This contrasts with Figure 11, where $TwitterUse$ alone is not able to produce a significant effect on Y_{Acts}, when $FacebookUse = 0$. $TwitterUse$ requires some level of $FacebookUse$ to have a significant effect on Y_{Acts}.

Figure 11: Twitter Use and Individual Acts of Participation, Conditional on Facebook Use

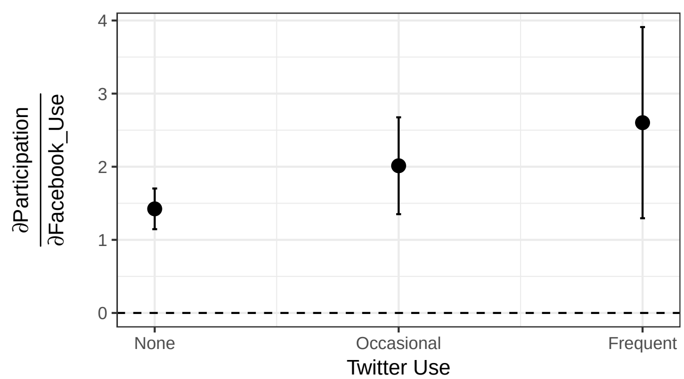


Conclusion and Discussion

This paper contributes two main findings to the literature. First, the social network structure of social media platforms matters when estimating their impact on political behavior. Second, social pressure is effective in promoting collective action. As individuals change how they chose to participate politically, researchers are presented with new opportunities to study the mechanisms

[20]Both the constituent term and the interaction term are used in the calculation of marginal effects. The coefficient of the constituent term will have impact on the marginal effect of that variable.

Figure 12: Facebook Use and Individual Acts of Participation, Conditional on Twitter Use



Note: Values in Figures 11 and 12 are conditional coefficients of the variables used in the multiplicative interaction term, derived from OLS regression estimates. Bars represent simulated 95% confidential intervals. A full table of regression estimates is available in Table 6, see Appendix.

that drive participation. Social media comes in a variety of forms, each composed of a unique network structure that determines the nature of the ties between individuals. Investigating the network structures that accompany various social media sites gives researchers the opportunity to compare causal mechanisms. The strong ties that exist between Facebook users encourage the transmission of social pressure, offering psychological selective incentives to engage in collective action. Twitter is comprised of weakly connected users, which facilitates information transmission. If the barrier to collective action is information based, Twitter can mobilize individuals. If free riding is the barrier to collective action, only Facebook can overcome the collective action problem through the platform's ability to transmit social pressure along network ties.

This theory is tested using survey data from participants of the 2011 Egyptian Revolution. Facebook Use had a significantly greater impact on political participation than Twitter use: Facebook users committed more acts of participation than Twitter users. Most importantly, the nature of this relationship is highly interactive: Facebook use increased the impact of Twitter use on the number of acts of participation committed. These findings provide evidence that social pressure could have mitigated the relationship found in prior studies between collective interest variables and participation. In the absence of social pressure, the impact of information availability does not affect the number of acts of participation committed. When the interaction term is included, the effect of Twitter use's constituent term (representing information availability) does not meet the threshold for statistical significance. The outcomes previously attributed to information variables may have been picking up the effect of social pressure variables, due to their interactive nature. When social pressure variables and the interaction occurring between the two variables are appropriately accounted for, information variables are no longer the most reliable predictor in the model. Their effect becomes dependent on the level of social pressure available. The differences observed between these models demonstrate the importance of correctly accounting for social pressure and the interaction with information costs.

Using a collective action framework, this paper explores *how* social pressure influences political participation. Previous literature has focused on the effect of information availability in motivating collective action. This approach fails to explain why individuals who would otherwise free ride choose to participate. Selective incentives offer a solution to the free rider problem. Social pressure, serving as a selective incentive, increases the payoffs associated with participation. When social pressure is introduced into the collective action model, a new payoff structure is created that alters preferences over the strategies available. If the social pressure term is greater than the cost associated with participation, the individual should participate. In prior literature, political participation has been inappropriately attributed to information variables alone, as social pressure makes free riders behave like conditional coordinators. This study finds that the relationship between participation and collective interest/information variables is dependent on the presence of social pressure. Using an interaction term in the model allows the constituent terms to measure the impact of one variable in the absence of the other. This approach allows researchers to determine with more clarity the independent effects of both mechanisms. These findings contribute to the debate in the collective action literature about the role of selective incentives-based approaches in explaining individual participation.

Both Twitter and Facebook Use produce change in individual behavior, yet this relationship operates along different causal mechanisms. The differences in network structure provide a test for which causal mechanism has more of an impact on protest participation: the effects of information transmission *or* social pressure. These mechanisms are explored using a social network approach to anticipate the impact of network ties on collective action outcomes. By mapping the network structure of social media platforms to strong-tie and weak-tie networks, researchers can test the influence of these mechanisms using the assumptions regarding information transmission and norm transmission. Twitter, with its weak-tie network structure, reduces the cost of information transmission and facilitates communication across even the most distant ties. Facebook employs a strong-tie network structure, transmitting social pressure to ensure adherence to social group norms.

The variation in the network structures of social media platforms offers different solutions to collective action problems. Twitter can promote collective endeavors when the barrier to collective action is the coordination problem. When the barrier to collective action is the free rider problem, the individual will rationally choose not to participate as they can receive the benefit without incurring any cost. Weak-tie networks will not change behavior in the face of the free rider problem; weak tie networks only impact the existing costs within the model. strong-tie networks, such as Facebook, can overcome the free rider problem as they provide psychological selective incentives in the form of positive and negative social pressures (social inclusion and social exclusion, respectively). The addition of selective incentives changes the payoff structure, making participation more attractive.

Awareness of the varying effects of social media platforms is essential to understanding political outcomes, as interactive communication technologies become ever more entrenched in daily life. Social science research has addressed the changing nature of Internet-based communication technology over the past decades, from its roots in private chat-rooms to the interconnected networks of Twitter. While researchers have striven to understand differences across time, the differences across virtual space are not fully realized. The Internet and social media platforms are continually evolving. Understanding how mechanisms in this space produce changes in behavior allows researchers, policymakers, and advocates to predict the impact of interactive communication technology on individual behavior.

3 STATUS UPDATE: ESTIMATING THE IMPACT OF SOCIAL PRESSURE ON VOTER TURNOUT USING SOCIAL NETWORKS PRESENT ON FACEBOOK

Abstract

This paper investigates the causal mechanism linking social media use and voter turnout through the social media platform's ability to supply social pressure, encouraging network members to follow social norms. Social media platforms with a strong-tie network structure are able to transmit complex social concepts including social norms associated with voting behavior. Social pressure is transmitted along the ties between an individual and members of their Facebook networks, supplementing influence received from face-to-face networks and information channels. The data for this study was collected by matching public Facebook user profiles to voter registration lists from four U.S. counties. Facebook use is found to have a positive effect on individual turnout. Specifically, individuals with high levels exposure to social pressure in their Facebook network are more likely to turn out to vote than those with low levels of social pressure in their online networks. This finding provides evidence that social media platforms with a strong-tie network structure provide access to social pressure. Social media's influence extends beyond the platform's ability to reduce information costs. Incorporating social network perspectives into research on social media and political outcomes may offer meaningful insights into enduring questions in political science, such as social media's role in political polarization.

Introduction

Social media's influence on political participation has gained considerable attention in political science literature. Models of individual choice often focus on individual-level variables, such as the cost of participation. Studies of social media's influence on participation typically focus on the information environment, specifically a platform's ability to reduce barriers to participation by providing access to political information at a low cost (Chadwick and Howard 2009). Online alternatives to traditional forms of participation are also available at a low cost through social media platforms (Margetts et al. 2015). Incorporating cost and the impact of the information environment is necessary when modeling voting behavior, yet focus on these factors alone ignores the impact of the social environment that social media platforms facilitate. The value of online social networks has already been explored in social capital literature, which finds that virtual activity positively contributes to social capital formation and political participation (Kittilson and Dalton 2010; Baumgartner and Morris 2010; Valenzuela, Park, and Kee 2009).

Henry Farell describes the internet as a "bundle of mechanisms that we can in principle disentangle from each other" (2012, pp. 36). Political outcomes are a product of many variables and causal processes. Applying this perspective to the Internet and exploring the multitude of causal processes within this environment will increase understanding of how technological changes impact political outcomes. As the popularity and relevance of individual platforms frequently change, ensuring that causal mechanisms remain the focus of research and not a particular platform is crucial. Understanding the underlying causal processes occurring in online environments will allow researchers to have a systematic understanding of how technology will impact human behavior, both in the present and future manifestations.

Causal mechanisms often link online networks and participation through the Internet's ability to alter the costs associated with collective action (Farrell 2012). In this paper, the causal mechanism is instead focused on the *extrinsic benefit* associated with participation. I argue that social networks provide additional incentives to engage in collective action based on an individual's desire to maintain their social standing. Individual and group behavior is inherently tied together: Individuals function as members of social groups and are heavily influenced by the values of those groups (Turner and Oakes 1986; Baumeister and Leary 1995). Extrinsic, social incentives alter the cost/benefit analysis associated with participation. Social acceptance becomes the benefit to participation for *individuals who would otherwise free ride.* These individuals are not motivated by electoral outcomes or intrinsic incentives, such as civic duty.

Social media networks differ in their network structures; researchers should be aware of the social structure present on the platform when assessing that platform's impact on behavior. Twitter, for example, focuses on information transmission between members of a diffuse, heterogeneous network. Modeling the effect of the information environment is appropriate for this type of network structure, as the platform is designed to reduce information costs. Conversely, models addressing networks structures that focus on strong social ties between individuals will need to incorporate social concepts into the analysis. Facebook is an example of a platform with a strong-tie network structure; networks are composed of homogeneous groups of individuals with close relationships to each other (Ellison, Steinfield, and Lampe 2007; Arnaboldi et al. 2012; Dunbar et al. 2015).

Individuals self-select into social media membership. Unlike face-to-face networks, either primary or secondary, social media use for personal purposes is voluntary. Individuals choose to use these platforms to pursue a goal. Uses and gratification approaches find that these goals include information seeking and dissemination, staying connected with face-to-face social networks, entertainment, and commerce (Baumgartner and Morris 2010; Shah et al. 2005; Li 2011). Even if an individual joins for entertainment or commerce goals, the inherently social structure of these platforms may incorporate that individual into social uses of the network. People join Facebook to participate in the process of social influence: Interpersonal goals include maintaining social connections with others and cultivating social status (Li 2011). Social science research finds evidence that behavior in one's online network has an impact on individual health and lifestyle choices, topics much closer to home than politics. Content posted by members of an individual's online network regarding drug use and sexual behavior has an effect on that individual's drug use and sexual behavior (Young and Jordan 2013; Huang et al. 2014). These findings noted that social media content altered the *perception* of social norms within a group. Social media can manufacture social pressure through repeat exposure to an idea, creating the appearance of a social norm within that group (Margetts et al. 2015). Users attach a social value to many online behaviors. Social value is associated with the number of friends a user has and the amount of "likes" and comments one achieves. Even after experiencing negative interactions while on these platforms, individuals continue to engage with the sites. These traits of users make determining the effects of social influence all the more important.

The influence of social pressure within online social networks has received little attention in Political Science literature. This paper contributes to research on the social environment by investigating social media networks and how the application of social pressure impacts individual voter turnout. The online network's ability to supply social pressure serves as the causal mechanism behind this relationship. Social pressure encompasses the process of social learning and diffusion of social information, as well as how group norms constrain behavior (Balbo and Mills 2011). Social pressure to follow group norms is provided by the social network and received by individual members. Social networks are homophilic; they determine the values of that group and guide the social behavior of their members (McPherson, Smith-Lovin, and Cook 2001; Abrams, Iversen, and Soskice 2011). Social pressure offers social rewards for following group norms while threatening those who resist with social sanctions (Abrams, Iversen, and Soskice 2011; Gerber, Green, and Larimer 2008; Gerber, Green, and Larimer 2010a; Green and Gerber 2010; Cialdini and Goldstein 2004; Panagopoulos 2010; Mann 2010; Gerber, Green, and Larimer 2010b; Davenport et al. 2010). Research has found that members of a network are willing to monitor and sanction the behavior of others (Ostrom 1998; Ostrom 2000). Social pressure derived from a Facebook network is not expected to be greater than the pressure within an individual's current face-to-face network; this paper argues that Facebook networks offer an *additional* source of influence.

Voting as a social norm is widely accepted in American Politics literature (Holbrook, Green, and Krosnick 2003). In 2012, over half the voting eligible population (58.6%) voted in the general election; further evidence that voting is a social norm (McDonald 2017). Social desirability response bias leading to overreporting of voter turnout in surveys demonstrates the importance of voting within social groups. Respondents are willing to lie about their voting record to match their behavior with socially approved behavior (Holbrook and Krosnick 2010; Abelson, Loftus, and Greenwald

1992; Karp and Brockington 2005). Individual voter turnout is also positively related to the *expected turnout of others* within that individual's social network (Abrams, Iversen, and Soskice 2011). Social pressure to vote is present within the social networks of Facebook, as these networks imitate offline networks and possess the strong-tie network structure necessary to deliver social pressure.

Facebook Use as a Measure of Social Pressure

This paper uses a more precise measure of Facebook use compared to prior studies that incorporated only an individual's presence on Facebook or other social media sites (Baumgartner and Morris 2010; Valenzuela, Arriagada, and Scherman 2014). In addition to the member's presence on Facebook, this measure incorporates unique elements of each user's online social network: the size and the number of years they are exposed to the network. A dichotomous measure of Facebook use does not allow for a clear test of social influence. Measuring general Facebook use incorporates all of the causal processes occurring on Facebook that may influence turnout, such as the platform's ability to provide low cost information. Past research has validated using the number of Facebook Friends per individual user as this allows researchers to observe variation in the independent variable (Valenzuela, Park, and Kee 2009). In this measure, the size of an individual's online network represents the variation in social pressure received through Facebook across users. The more ties an individual has to others, the more opportunities that individual has to encounter social pressure transmitted along those ties. Larger networks offer more exposure to social pressure (Centola and Macy 2007; Centola 2010). Smaller networks are not able to provide exposure to social pressure to the same extent. Greater changes in behavior are expected to occur among individuals with large networks than among those who have small networks. This difference is due to variation in the amount of social pressure received.

While content-based approaches may allow researchers to analyze messages of social pressure directly, this method is unable to measure individual-level characteristics such as past vote history, age, party identification, and gender. These characteristics have an impact on political behavior; their inclusion is critical when modeling voting behavior. The sample used in this study is pulled from voter registration lists, providing demographic information for each observation. Another issue with the content-based approach of measuring social pressure stems from the privacy features of Facebook. Users choose which information they make public, often times researchers will not have access to a user's Timeline or Newsfeed features. The platform's attributes catalog the messages that individuals send and receive. This setting contrasts with Twitter, where researchers have more comprehensive access to the tweets posted by the individual and their Twitter network. The goal of this paper is to measure a strong-ties network, of which Facebook is the best example. Therefore, the data must be gathered using the publicly accessible user information on Facebook.

Using Facebook as a source of social pressure to follow group norms requires evidence that: 1) Facebook networks offer exposure to social norms and social pressure, and 2) individual members are active and engaged with their networks on Facebook. Engagement is necessary to receive social pressure from the platform.

1. Facebook Networks Offer Exposure to Social Norms

Facebook is a social media platform composed of *strong* ties between individuals and has the ability to offer exposure to social norms and pressure. This paper uses both the *strength of weak ties* and the *strength of strong ties* hypotheses to address the tie structure found in social media platforms, specifically how these networks transmit information (Valenzuela, Arriagada, and Scherman 2014). The strength of strong ties hypothesis states that strong ties are necessary to produce changes in behavior, as these ties support the transmission of complex social concepts (Centola and Macy 2007; Centola 2010; Valenzuela, Arriagada, and Scherman 2014). Strong ties exist in primary groups, composed of family and close friends within an individual's offline, face-to-face network. Previous research finds that an individual's Facebook Friends consist of the same members found in their offline social groups (Ellison, Steinfield, and Lampe 2007; Arnaboldi et al. 2012). The network structures that exist in these face-to-face ties are also found in online networks (Dunbar et al. 2015). Facebook friend networks are an extension of offline social networks. The similarity between a Facebook network and an offline social network supports the postulation that social norms present in face-to-face groups are also present online.

Facebook networks represent a large *collection* of primary networks. The Facebook platform allows users to easily maintain virtual connections with members of past face-to-face networks, even as individuals undergo drastic life changes (Ellison, Steinfield, and Lampe 2007; Lev-On 2010). Graduating from school, changing jobs, or moving residences increases the cost of maintaining relationships attached to prior face-to-face networks. Reducing contact between members of a network weakens the strength of that tie. The ability to maintain connections via Facebook allows for strong ties to endure outside of a current face-to-face network. Facebook networks provide access to *multiple* primary networks, offering another avenue for exposure to social pressure. In addition to connecting individuals to their primary networks, Facebook users may maintain connectivity with members of secondary groups: acquaintances and other socially distant contacts. These relationships represent weak ties, which are more efficient at spreading information than social behavior (Centola 2010). Members of secondary groups are not identified in this dataset; these individuals will dilute the effects of social pressure observed.

While the strength of strong ties hypothesis states that social pressure serves as a causal force behind behavior change, the strength of weak ties hypothesis posits that weak-tie networks are better able to change behavior through their capacity to spread information across distant ties (Granovetter 1973).[21] This paper does not disagree that weak-tie networks facilitate political participation through their ability to provide the political information necessary to organize and act. However, I propose that these effects are limited to individuals who are already interested in participating; political information alone will not change the cost/benefit analysis associated with participating for individuals who would rather free ride (Ostrom 2000). Strong-tie platforms are more efficient at *changing behavior in individuals otherwise not inclined to act*. Strong-tie network structures provide social pressure to abide by those norms, overcoming the free rider problem.

The inability for changes in costs alone to spur participation in elections is evident in the behavioral response to voting reforms. Reforms such as early voting, election day registration, and voting by mail attempt to increase turnout by decreasing costs associated with registering and voting. Research has found that most reforms only make voting easier for those already interested in participating, they do not stimulate new voters (Burden et al. 2014; Thompson 2004; Berinsky 2005; Neiheisel and Burden 2012). AJ Berinsky advises that to see changes in turnout among nonvoters, reforms must shift away from institutional practices towards engagement and mobilization to "make people want to participate" (Berinsky 2005). Voter registration requirements in the US also do not have the large negative effects one would expect if cost was the single most important factor associated with participation (Ansolabehere and Konisky 2006; Burden and Neiheisel 2013). In the absence of changing peoples' interest in voting, social networks can provide alternative incentives to vote besides interest in the outcome of the election.

Social media's impact on individual turnout is expected to vary across subgroups: The social norm of voting varies according to values associated with that group. Subgroups may be based

[21] A concern is that Facebook use is capturing political information transmission. Granovetter's argument states that tightly knit, homogenous networks limit the amount of information that individuals encounter (1973). The structure of strong-tie networks reduces new information received, making information redundant in tightly knit networks. The characteristics of Facebook label the platform as a strong- tie network, limiting the effect of information transmission. Any change in behavior observed from the Facebook network is due to social pressure, not a reduction in information costs.

on SES, age, ethnicity, religious attendance, etc. (Abrams, Iversen, and Soskice 2011). Research addressing overreporting of voting in surveys provides evidence for social pressure effects between groups. The overreporting of voter turnout occurs with individuals who are members of groups that value voting (Silver, Anderson, and Abramson 1986). Overreporting is not present in groups where voting is not a social norm. The method of data collection used in this study controls subgroup differences by limiting the sample to registered voters. This dataset consists of ego networks; each ego (individual) is a *registered voter*, with many having voted previously. Strong-tie networks are homogeneous in nature; these individuals are assumed to belong to networks where voting is a social norm. This characteristic limits variation in the value of voting across networks in this sample, compared to samples that would contain the voting *eligible* population.[22] To test how social pressure influences the sample of registered voters who are already predisposed to vote, this study measures *variation in exposure* to social pressure. The level of social pressure available within each online network is directly measurable by the network's size and the number of years that individual has been a member of Facebook.

Social norms regarding participation are communicated through social interaction (Abrams, Iversen, and Soskice 2011; Putnam, Leonardi, and Nanetti. 1993). The relationship between social interaction and political norms also extends to online social interaction (Dalton and Kittilson 2012; Kittilson and Dalton 2010). The internet provides an array of interpersonal networking opportunities including social networking sites such as Facebook, where individuals feel a connectedness to others (Valenzuela, Park, and Kee 2009; Dalton and Kittilson 2012). Individuals are able to use low-cost online resources to engage in political discussion with peers (Margetts et al. 2015). Facebook offers a variety of features enabling users to interact with their network and receive information on social norms. Users can view their network's posts and comments using the Newsfeed feature. The

[22] The Voting Eligible Population includes both those registered to vote and those who are not registered but can legally vote in US elections. This measure excludes non-citizens and ineligible felons (McDonald and Popkin 2001).

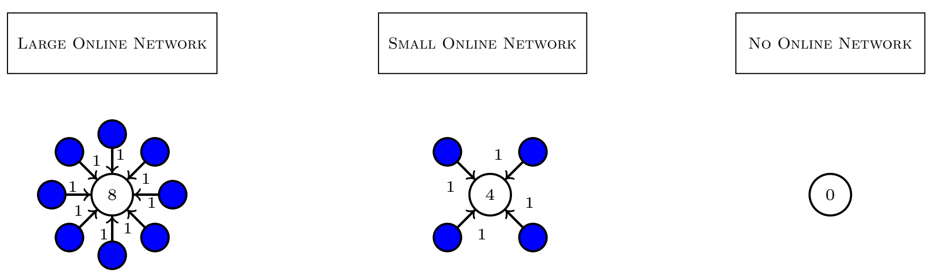
Newsfeed refers to a chronological ordering of the activity within a user's Friend network. Each user has access to a unique Newsfeed depicting the recent activity of their peers. Network activity includes posts, comments on posts, and "likes", which are available for viewing on the Newsfeed. Posts consist of photos, original written content, and "sharing" (forwarding) content created by others, including "memes".[23] A Facebook "like" refers to the action of clicking a thumbs-up ( ) button within the post to indicate positive sentiment towards that post, comment, etc. Users can "tag" each other in posts, publicly linking another user to posted content. Users also view their Friends' individual Timelines. A Facebook Timeline is the chronological ordering of a single user's activity, accessible on their individual Facebook profile.

To influence behavior, it is necessary to receive social pressure through multiple members of an individual's network (Centola and Macy 2007; Centola 2010). Individuals require contact with *multiple* sources of social pressure in order change their behavior. The more Facebook Friends a user has, the more social pressure that user will receive from their online network. Figure 13 illustrates this measure using a simple network graph. The solid, blue nodes represent "alters", members of an individual's online Facebook network. The total number of alters within one network is measured as "Friend Count" in the dataset. The white nodes represent the "egos", or individual Facebook Users. These nodes represent the individual observations within this dataset. Each alter (blue node) can transmit a "unit" of social pressure across alters, which is consistent in strength. Each blue node in Figure 13 transmits one unit of social pressure to the white node. This transmission occurs along the tie between nodes. Note that the direction of the arrow indicates that the unit of social pressure is *received* by the ego (Facebook user). This characteristic represents the direction of influence between the independent variable measuring Facebook use, and the dependent variable measuring individual voter turnout. In a true strong- ties network, this relationship is reciprocal.

[23] A meme is an image, often consisting of a written text imposed on a photo. Memes are usually humorous or satirical. They are spread across the Internet to convey a message.

This example visualizes how the variation in social pressure received by each ego in the sample is due to the numbers of alters in that network. In Figure 13, the large network on the left of the diagram transmits eight units of social pressure to the Facebook User, one unit per alter. The small network in the center transmits only four units of social pressure. The lone node on the right represents individuals who do not have a Facebook account; they receive zero units of social pressure from an online network. Individuals in the sample who are not members of Facebook are coded as having zero Facebook Friends, as they receive no social pressure from an online network. Highly populated networks offer a greater number of ties, providing each user with more exposure to social pressure. Less populated networks have fewer ties, supplying less exposure to social pressure.

Figure 13: Transmission of Facebook Pressure in Large and Small Networks

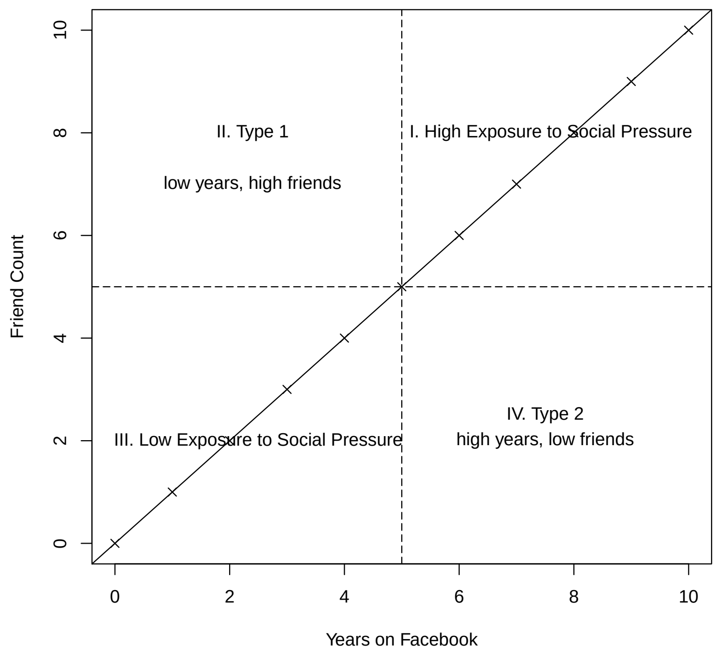


The assumption that large Facebook networks will provide more social pressure than small networks is at odds with traditional arguments regarding group size in collective action theory. Addressing network size is relevant in this study as Facebook networks can become extremely large compared to offline networks. Olson argues that small groups promote collective action due to their ability to monitor the behavior of group members. Olson hypothesizes that large groups may be able to provide the same pressures as face-to-face groups if they can "continuously bombard" individuals with information (Olson 1965). However, in the pre-Internet era, Olson sees the costs of providing this information as prohibitive. The influence of group size on behavior within online networks becomes a critical question, as changes in technology alter the assumptions of group size on individual behavior (Margetts et al. 2015). Incorporating technology's ability to reduce the costs associated with monitoring behavior and applying rewards or punishments advances Olson's theory (Lupia and Sin 2003; Lev-On and Hardin 2008). Advances in technology allow large groups to mimic small group effects, supporting the assumption that large Facebook networks will influence individual behavior.

Measuring Engagement on Facebook

Using Friend Count alone to measure social pressure is problematic as individuals differ in the way they use Facebook (Ugander et al. 2011). Facebook is typically used as a strong-tie network whose members maintain intimate relationships developed over time. However, users may employ the platform for non-traditional purposes such as information gathering or distribution, characteristics of a weak-tie network. Some users have amassed large Friend counts but are only recent members of Facebook, indicating that they have not developed close social ties with their Facebook network. In these cases, users are not socially close to their Facebook Friends; the network primarily consists of weak-ties. These individuals are using the Facebook platform similarly to how one would employ Twitter or Instagram. For example, a goal of some Instagram users is to become "Instagram famous", a reference to otherwise ordinary users who have reached "microcelebrity" status through their ability to amass thousands of followers (Marwick 2015). For this reason, it is important to measure the user's level of intimate engagement with their Facebook network. Prior research measures engagement based on 1) user friend count, 2) time spent on Facebook and 3) reports of attachment to the social media platform (Ellison, Steinfield, and Lampe 2007; Valenzuela, Park, and Kee 2009). The authors collected this data via survey. While the dataset used in this paper provides information on friend count and the number of years a user has had a Facebook account, it is unable to incorporate reports of individual attachment due to the reliance on publicly available information.

Figure 14: Type of Facebook Use Compared to Pressure Received



The *interaction* occurring between the number of Facebook Friends within an individual's network (herafter, $Friends$) and the number of years an individual has been a member of Facebook (herafter, $Years$) produces the measure of social pressure used in this analysis. Using both $Friends$ and $Years$ is crucial when estimating the effect of social pressure received via a Facebook network. Individuals who may identify as recipients of high levels of social pressure according to one of the variables may not be intimately engaged with their Facebook network. Quadrants II and IV in Figure 14 portray these hybrid users. Type 1 and Type 2 users do not use the Facebook platform traditionally and likely receive little social pressure through their Facebook network. Using an interaction term consisting of $Friends$ and $Years$ allows the level of social pressure received to be attributed to users accurately.

Type 1 users, found in Quadrant II in Figure 14, have had Facebook for a short amount of time, yet they have developed an unusually large network of Facebook Friends. Type 1 users are likely to attach social value to achieving many followers and distributing information *to* their network versus creating strong ties enabling them to receive social pressure *from* their network. The weak ties that exist in these networks are not likely to transmit much social pressure. Using $Friends$ alone may falsely attribute users with high $Friends$ values and low $Years$ values as recipients of social pressure, biasing the results. The product term takes into account the low $Years$ value, offering a score that more accurately displays the amount of social pressure they receive. Type 2 users had a Facebook account for many years but accumulated only a small number of Facebook Friends. These users are shown in Quadrant IV in Figure 14. These members are not likely to be active as they have not taken the time to develop their online network, evident by a low $Friends$ value. Using only $Years$ assumes that these individuals received high levels of social pressure, again biasing the findings. The product term accounts for the low $Friends$ value, decreasing the social pressure score to appropriately reflect the low levels of social pressure received from the user's network.

Quadrants I and III (Figure 14) correctly identify the amount of social pressure that users should receive if their use of Facebook adheres to the strong-tie network structure of the platform. Traditional Facebook users who have had an account for many years are more likely to have substantial friend networks that have cultivated organically over the years. When an individual adopts Facebook, they will connect with members in their face-to-face network. As their relationships change and new people enter their face-to-face network, their online network will increase in size. Users can reacquaint themselves with past face-to-face networks that were too costly to maintain prior to the adoption of Facebook. Additionally, veteran Facebook users are likely to be more skilled at using the platform and have integrated Facebook into their daily or weekly routine, increasing exposure to the online platform. Users in Quadrant III experience low exposure to social pressure due to being relatively new adopters of the platform with low $Friends$ values. This effect contrasts to

Quadrant I, where users experience greater exposure to social pressure due to high $Friends$ values and high $Years$ values.

Introducing Social Concepts into Rational Choice Theory

This paper utilizes a rational choice framework, extended to allow extrinsic incentives to be incorporated in the utility function (Gerber, Green, and Larimer 2008). Applying behavioral concepts to rational choice theory improves the predictive power of these models, as they are better able to explain human behavior accurately. In the traditional calculus of voting model, a citizen will vote if: [24]

$$p(B) + D > C \tag{2}$$

Participation depends on the utility an individual receives from the available alternatives, voting or abstaining. The B term in Equation 2 represents the candidate differential, the benefit received from the electoral outcome. This benefit derives from an individual's preferred candidate being elected over the competition. The p term measures the probability that an individual's vote will have an impact on the outcome of the election. This term is calculated as the probability that a candidate will win when individual i does (or does not) vote in an election with v voters (Riker and Ordeshook 1968). In an election where v is equal to millions of voters, the probability of being pivotal is near zero due to the size of the electorate (Feddersen 2004). The cost of voting, C, is associated with the act of voting itself (Riker and Ordeshook 1968). Costs include investing effort in becoming registered, acquiring information on the candidates, and turning out to vote. The higher the costs associated with voting, the less likely the person is to vote (Downs 1957). If $p(B) + D$ cannot overcome the cost associated with voting, abstaining is the dominant strategy. If the citizen chooses to abstain, they still receive the benefit from others voting without incurring any of the

[24] Initially stated by Downs and updated by Riker and Ordeshook (1957; 1968)

costs. This outcome is detailed in Figure 15.

Downs argued that the costs cannot become low enough to validate the choice to vote as the probability of being pivotal is almost zero, introducing the "paradox of voting" (1957). Rational actors should abstain, yet millions of citizens choose to vote. Despite the difficulties that the calculus of voting model has in explaining turnout, evidence shows that individuals behave strategically when deciding to vote. For example, increases in the cost of voting decrease turnout (Wolfinger and Rosenstone. 1980; Gimpel and Dyck 2005). Additionally, individuals are more likely to vote if they perceive the election to be close (Blais 2000). The application of social concepts to rational choice models has evolved to better equip this theory in explaining individual voter turnout (Aldrich 1993; Blais 2000; Feddersen 2004; Gerber, Green, and Larimer 2008). The addition of the D term allowed the model to predict turnout, yet more effort must be directed into fleshing out the causal processes that result in turnout. Relying on "civic duty" as an explanation has been criticized in the rational choice literature (Barry 1970; Aldrich 1993; Feddersen 2004). If an individual chooses to vote because they value voting, the question changes to *why* they value voting. This question is not directly answered using the existing D term (Barry 1970).

Mobilization models also struggle to explain why rational, self-interested voters choose to vote rather than free ride. In mobilization models, group leaders increase turnout by reducing the cost of information for individual voters and increase the B term by organizing a voting block (Feddersen 2004). Voting as a group increases the chances of being pivotal in a large electorate. However, leaders in large groups face difficulty with monitoring individual behavior. Furthermore, in a democracy such as the US it is difficult, if not illegal, to apply tangible rewards or sanctions associated with voting. Group mobilization theories, along with the "civic duty" explanation, cannot explain why an individual may be motivated to vote if they do not care about the election outcome.

To make turnout rational, models must involve extrinsic motivators, not just intrinsic motivators

(Harbaugh 1996). Extrinsic incentives offer a stronger explanation for turnout; these incentives include social acceptance obtained from following the social norms of voting. Incorporating social influences into the rational choice framework allows individuals to include social considerations in their utility function. Gerber, Green, and Larimer propose a modification to the traditional calculus of voting model that includes both intrinsic and extrinsic motivations (2008). An individual will vote if:[25]

$$p(B) + D_I + D_E > C \tag{3}$$

D_I in Equation 3 represents intrinsic motivators, such as civic duty. Extrinsic factors, D_E, embody the social aspect of voting, specifically social pressure. Information on the importance of an election is delivered via political discussion within a social network (Abrams, Iversen, and Soskice 2011). Social pressure to vote encompasses both the act of seeking social approval as a reward for voting and the act of avoiding social disapproval from abstaining (Gerber, Green, and Larimer 2008; Abrams, Iversen, and Soskice 2011). For example, an individual may be rewarded by being included in more group activities or being regarded as more trustworthy. Social sanctions involve being excluded from group activities or being perceived as less trustworthy. Social approval and disapproval are administered by informal social networks; group members are willing to punish others for deviations from accepted behavior (Ostrom 2000). Social pressure presents a micro theory of how individuals influence each other within small, non-pivotal groups. According to social pressure theories, the utility from voting stems from social rewards– not from tangible rewards, the candidate differential, or intrinsic rewards including adherence to one's civic duty (Abrams, Iversen, and Soskice 2011; Feddersen 2004). The incentive to vote derives from the desire to maintain a desirable standing in the community. With the addition of D_E, voting becomes the dominant strategy (Figure 16). Social pressure theories of voting complement the existing calculus of voting model, working alongside the

[25] For this paper, the model is simplified.

Figure 15: Utility of Voting Model

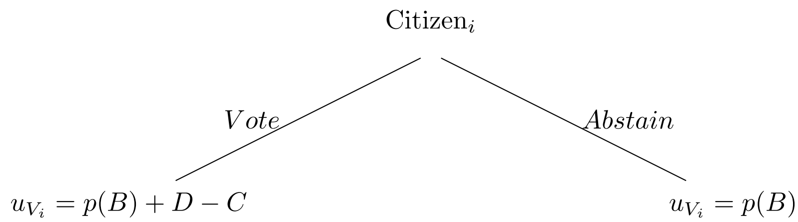
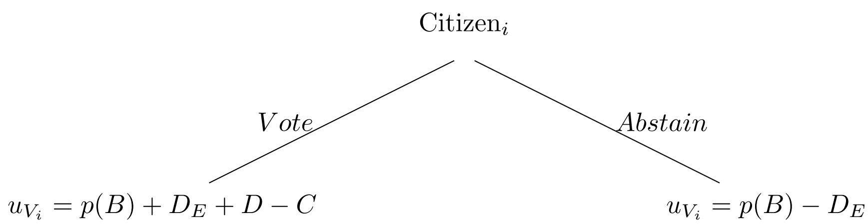


Figure 16: Utility of Voting Using Extrinsic (Social) Incentives



benefit and cost variables while improving the ability of the model to explain individual turnout.

Though the measure cannot exclude influence from intrinsic motivators such as civic duty, the majority of the impact is expected to stem from social pressure. When the D term is broken down into its intrinsic (civic duty) and extrinsic (social pressure) components, the impact from social pressure was significantly greater than the impact from civic duty (Gerber, Green, and Larimer 2008). Gerber, Green, and Larimer found that priming a subject with a social pressure treatment increased turnout by 8.1%, while priming them with a civic duty treatment increased turnout by only 1.8%.

Social Pressure Online

The characteristics of Facebook's network structure enable this platform to provide extrinsic incentives. Facebook is made of the same individuals found in a user's current and former face-to-face networks; the social pressure distributed by a user's network has real-world consequences. Users intentionally join online social groups to connect with others; social media use is directly related to giving and receiving social influence to attain intangible, social rewards. The uses and gratifications approach includes many goals associated with an individual's online activity, including information seeking and dissemination, staying connected with face-to-face social networks, entertainment, and commerce (Baumgartner and Morris 2010; Shah et al. 2005; Li 2011). Interpersonal goals include maintaining sociability and social status (Li 2011). Sociability consists of the social relationships one has with others, while social status consists of the respect, influence, and prominence an individual maintains within their social group (Baumeister and Leary 1995; Anderson et al. 2001).

If people are joining social media platforms to engage socially, how do these platforms shape individual behavior through social influence? The investigation here states that social pressure on Facebook *supplements* the pressure exhibited in face-to-face groups that the platform mirrors (Dunbar et al. 2015). This study cannot investigate internet-specific social incentives or punishments, nor are they required theoretically. However, as humans increasingly use social media platforms to manage their social life, online rewards and sanctions need to be addressed.

For online rewards and sanctions to be effective, users must value their social standing within the online community. The importance that users attach to online networks is demonstrated by social media's impact on both self and social worth. Facebook use, specifically, has an impact on self-esteem (Gonzales and Hancock 2011; Valkenburg, Peter, and Schouten 2006). For example, a user's presentation of their self to others and reminders of their social connections via Facebook has a positive impact on individual self-esteem (Gonzales and Hancock 2011). Social media use also impacts *social* self-esteem, the self-worth linked to one's social value or social standing. The sentiment of the feedback received online also affects one's social self-worth. Feedback includes comments, posts, shares, likes, and tags distributed on a social media platform. Negative feedback reduced social self-esteem, while positive feedback improved a user's social self-worth (Valkenburg, Peter, and Schouten 2006). The number of friends a user has is publicly visible and has an impact on popularity and social attractiveness. As a user's friend count increased, they became more socially attractive to others (Tong et al. 2008). The relationship was curvilinear- users with "too many" online friends made others doubt their actual popularity.

Social media also creates changes in behavior due to online incentives or punishments. Perhaps the most glaring example is the impact of cyberbullying, which is linked to increases in suicidal thoughts and actions in young individuals (Hinduja and Patchin 2010). Social media users also show changes in online behavior, updating their profiles to increase the chances that they receive positive feedback versus negative feedback (Valkenburg, Peter, and Schouten 2006; Ellison, Heino, and Gibbs 2006). Users will adapt to others' cues of socially desirable behaviors received via feedback available on the platform. Research finds that despite feeling negative emotions when accessing social media platforms, users continue to engage online due to "Fear of Missing Out", or FoMO. FoMO is a "pervasive apprehension that others might be having rewarding experiences from which one is absent", causing individuals to feel compelled to stay connected with others (Przybylski et al. 2013). The ease in which one can access others via social media exacerbates this phenomenon. Increases in negative emotions and FoMO correspond with increases in engagement on Facebook (Przybylski et al. 2013).

These findings demonstrate that online social networks have a real impact on the behavior of their members. Facebook can provide both social rewards and punishments resulting in behavior change; social pressure functions similarly in online networks as it does in offline networks. Though

Facebook's features are continually changing, current social rewards include maintaining and increasing one's friend count and accumulating likes, tags, shares, and positive comments. Social punishments involve receiving negative comments, losing Facebook friend connections, or a reduction in the number of likes, tags, shares, and positive comments received.

Data

This dataset consists of a random sample of 1,000 registered voters drawn from the voter registration rolls of four U.S. Counties: Wake County, North Carolina, Oklahoma County, Oklahoma, Miami-Dade County, Florida and Erie County, Ohio. These counties were selected in part due to the availability of voter registration data, as well as obtaining a sample that is most representative of the U.S. Before the 2012 General Election, a random sample of 250 residents was drawn from each county's voter registration roll. Though using voter registration rolls limits the analysis to only those who are registered voters, this approach was necessary to verify turnout and obtain demographic information. This information was essential for locating the Facebook user and serving as control variables in the study. This approach offers conservative estimates of Facebook's effect on voting behavior as these individuals are already likely to vote. Any change observed in the dependent variable will provide strong evidence of the effect of Facebook use.

The Facebook search engine and a list of verification criteria from the voter registration lists were used to detect if voters had a Facebook account. This step was hand coded to ensure accuracy. Verification categories included first name, last name, middle name, suffix, city, and age. Each category was allotted an individual score; the total across categories served as the final verification score. Facebook accounts had to achieve a verification score of seven or greater to qualify as the registered voter from the sample. For example, a Facebook user whose first name (three points), last name (three points), and location (two points) matched that found in the voter registration list achieved a verification score of eight. This score is high enough to confirm that the Facebook user and registered voter were a match. The codebook is found in Appendix 6. Through this process, 38% of the voters in the sample were matched to Facebook profiles in 2012 and 41% in 2014. In addition to recording the presence of a Facebook account, the number of Facebook Friends and the year that the user adopted Facebook was recorded using the timeline feature. In addition to profiles that did not meet the verification threshold, some matches may have been missed due to Facebook's privacy settings: Users can make their names unsearchable. The limitations of the data collection process ensure a conservative estimate of Facebook use, as users are likely underreported. This information was gathered again in 2014 to determine if previous Facebook users still had a Facebook profile, as well as if any previous nonusers had created an account.

After the 2012 election, voter registration lists were collected to incorporate the 2012 General Election results into the dataset. This process was repeated for the 2014 Election. A drop-off was observed from the pre-election to post-election sample of registered voters. Registered voters are removed from the rolls due to death, a felony conviction, changing residence, registering in another county, or lack of voter contact. The criteria for removal varies by county. Table 3 provides descriptive statistics for the Facebook data. The percentage of Facebook users in the sample increased from 38% in 2012 to 41% in 2014, this is expected as the popularity of social media platforms has increased. The average number years an individual Facebook user has an account ranged from three years in 2012 to 4.5 years in 2014. Descriptive statistics for all variables used can be found in Table 9 in in Appendix 3.

Figure 17 depicts Facebook use among voters and nonvoters. As expected, more individuals in the sample of registered voters chose to vote rather than abstain from voting. Of the voters in the sample, 40% were Facebook Users. Rates of use dropped to 35% among nonvoters. The relationship between Facebook use, age and voter turnout is pictured in Figure 18. Age cohorts are represented by 10-year intervals with exceptions for 18-22-year-olds and individuals age 79 and older. The 18-22-year-olds are a unique group as they are new to voting and are habitual social media users, compared to other groups who were not socialized into social media use until their teens or later. Facebook use above age 70 is very small, so these age cohorts are combined. The distribution of voters among the age groups follows traditional findings; voter turnout increases by age until it drops off among the oldest voters. Facebook use in the sample follows a pattern: In Figure 19, the gray dashed line demonstrates that Facebook use decreases as the cohorts increase in age. This pattern follows general trends in social media use (Pew 2018a). This trend is also visible when the sample is limited to voters only, depicted in the blue line in Figure 19. Facebook use decreases steadily as the cohorts increase in age. Voters tend to use Facebook at higher rates than nonvoters, with the interesting caveat occurring among the 18-22 age cohort.[26] In this group, where social media use is the most prevalent, Facebook use is evenly split among voters and nonvoters. Age cohorts not only use Facebook at different rates, but also this data suggests that the way age groups are influenced by social media use also differs. Future research should further explore the effects of age and social media use on political behavior.

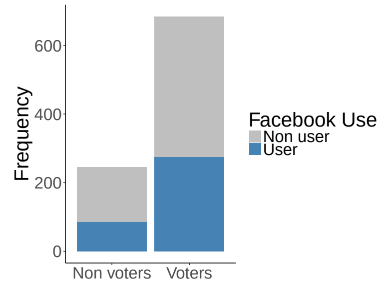
Table 3: Facebook Data

	2012	**2014**
Turnout	74%(680)	48%(405)
Facebook Users	38%(381)	41%(400)
Average Years on Facebook	3	4.5
Drop-off from Original Sample	9%	17%

In 2012, the average user in our sample had 172 Facebook Friends and had spent almost three

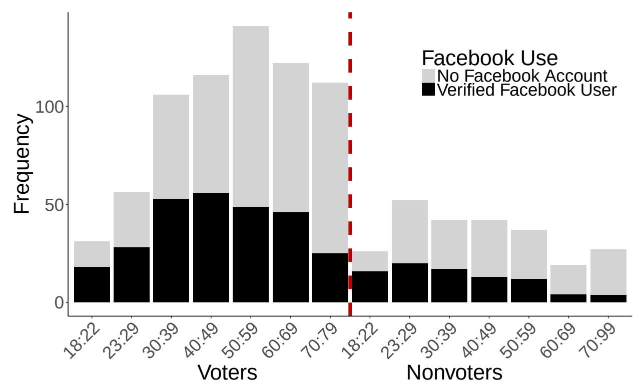
[26] Of the voters in the 18-22 age cohort, 47% had Facebook. This decreased to 12% of those age 70 and older. An interesting trend occurs with Facebook use when the sample is limited to nonvoters, depicted in the black line in Figure 19. A large difference in use is observed between the 18-22 age cohort and the other cohorts. Among the voters in the 18-22 age cohort, 48% had Facebook; this is greater than the percentage of voters with a Facebook account. Within the 23-29 age cohort, use drops to 29% of nonvoters, a 12 point decrease from the (41%) of voters with an account. The percentage of Facebook users continues to decrease, with the exception of a spike among 50-59-year-olds.

Figure 17: Facebook Use and Voter Turnout



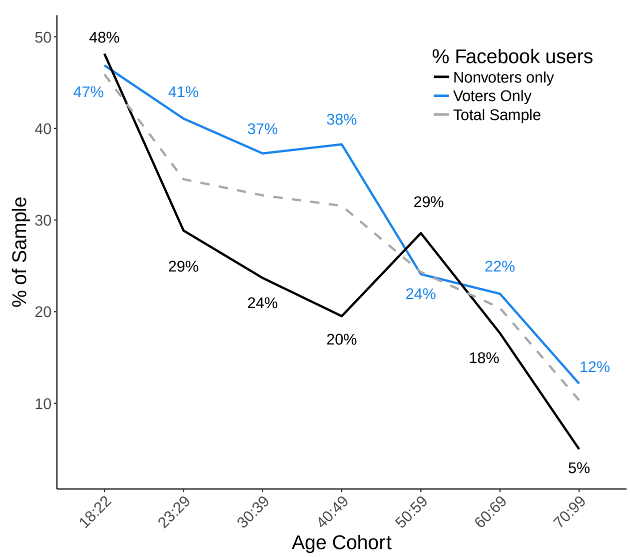
Notes: Data is from the 2012 election.

Figure 18: Frequency of Facebook Use and Voter Turnout by Age



Notes: The red dashed line splits the data between voters and nonvoters. Data is from the 2012 election.

Figure 19: Frequency Facebook Use and Voter Turnout by Age



Notes: The percentages are rounded, exact percentages can be found in Table 10 of Appendix 3. Data is from the 2012 election.

years on Facebook. To investigate trends in the data, Table 4 places users into one of eight categories based on their number of Facebook Friends. Seventy-five percent of the sample had less than 400 Friends. Only 6% of users had more than 1000 Friends in their network. Higher friend counts were associated with younger users, see Figure 20.[27] Users 49 years old or younger had an average Friend count of 415, while users 50 and older had an average Friend count of 106. In 2012, 88% of the sample had a Facebook account for four years or less.[28] Younger users tend to have had a Facebook account for a longer amount of time (Figure 21). Users 49 years old or younger had Facebook for and an average of 1.5 years, while users 50 and older had Facebook for less than a year. As Facebook Friend Count increases, the number of years that a user has had a Facebook account also tends to increase.[29] This trend shows that most individuals on Facebook build their networks over a series of years. This relationship is consistent with our concept of social pressure and its distribution throughout users as displayed in Figure 14. Most Facebook users in our sample fit into the high or low social pressure categories in Quadrants I and III, with fewer hybrid users captured in Quadrants II and IV (Figure 14).

Table 4: Friend Count Per User

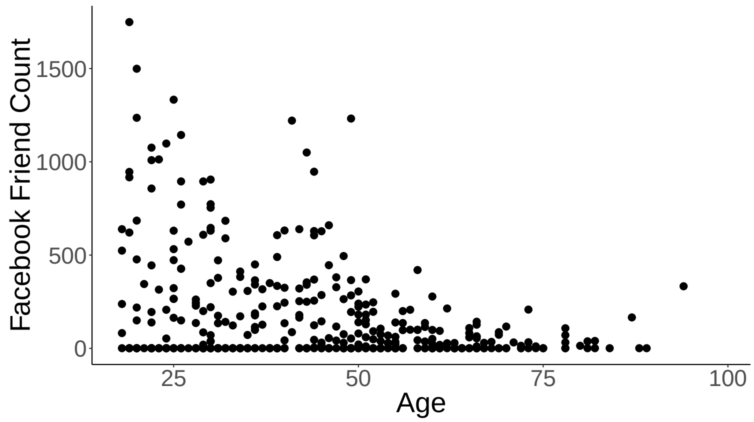
Friend Count (Category)	% of Users
1 : 49 Friends	18 %
50 : 99	14
100 : 199	19
200 : 299	13
300 : 399	11
400 : 499	6
500 : 999	13
1000 : 1749	6

[27]See Figure 49 in Appendix 3 for a breakdown by age category and Friend Count Category.

[28] Table 17 (Appendix 7) displays the percentage of Facebook users who have had Facebook from one to seven years; seven years is the longest amount of time a user in our sample had Facebook.

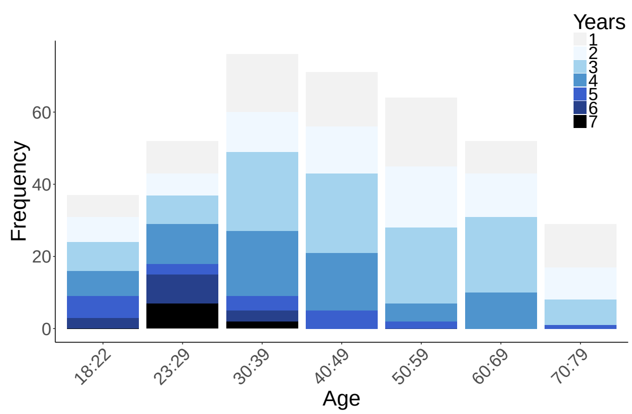
[29] In Figure 50 (Appendix 7), the dashed blue line depicts the linear relationship between Facebook Friend Count and Years on Facebook for Facebook users within the dataset.

Figure 20: Friend Count and Age Plot



Note: Data is from the 2012 election.

Figure 21: Years on Facebook Per User (By Age)



Note: Data is from the 2012 election.

Figure 22 characterizes Facebook use and Voter turnout by gender. Female registered voters accounted for 53% of the sample. Of those who did turn out, 56% were women, 44% were male. More voting women had a Facebook account compared to voting men, 33% vs. 21%, respectively. The reverse is seen among nonvoters: Of nonvoting women, 23% had a Facebook account; of non-voting men, 28% had a Facebook account. In the sample, women, in general, were more likely to have a Facebook account, 29% of all women versus 22% of all men. Of Facebook users, 62% were female. On average, women tend to use social media platforms at slightly higher rates than men (Pew 2018a). The difference is highest among Facebook users, but disappears for Twitter and

Table 5: Years on Facebook (per User)

Years on Facebook	% Facebook Users
1 Year	19 %
2	20
3	30
4	18
5	6
6	4
7	2

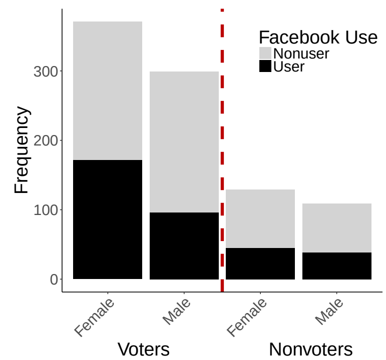
LinkedIn, an information and business based platform. These results raise two questions, 1) do females use social media platforms for different purposes than men and 2) do female users receive more social influence from social media platforms than male users? Research has found mixed results differences in the effect of social influence between men and women; some findings point that women may be more susceptible to social influence then men (Krupnikov, Milita, and Ryan 2016). Future research should explore the effects of gender and social pressure, specifically the effect of social media use.

Figure 23 depicts how Facebook use and Voter turnout varies across party identification. This category consists of Republicans, who represent 32% of the sample of registered voters, Democrats at 35%, and "Other" at 33.2%. Other consists of unaffiliated voters, missing data, and Independents, as the later represents only 3% of all registered voters in the sample.[30] Turnout rates for Republicans and Democrats was fairly even in the dataset, 81% and 82% respectively. Turnout among "Other" was 60%. Among voters, 26% of Republican had Facebook, 30% of Democrats and 30% of "Other". These rates were comparable to nonvoters.

It is important to note the difference in turnout between the 2012 and 2014 elections. The 2012 election was a presidential election, where turnout is significantly higher than midterm elections.

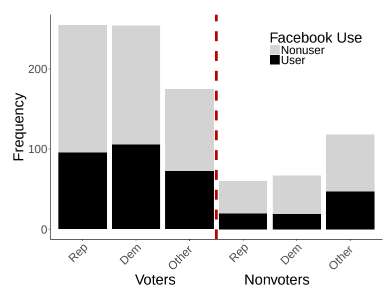
[30] Individuals in the sample in the "Other" category tended to be younger, but they were evenly distributed over gender (as were parties in general in this sample). Sixty percent of Erie County's 250 registered voters were listed as "Other"; this was due to missing data. Miami-Dade County's "Other" voters totaled 22% of the 250 observations from this county; they consisted of unaffiliated voters. Wake County's 32% "Other" voters were also listed as unaffiliated. Fourteen percent of Oklahoma County voters were registered Independents. These individuals were included in Other.

Figure 22: Frequency Facebook Use and Voter Turnout by Gender



Notes: The red dashed line splits the data between voters and nonvoters. Data is from the 2012 election.

Figure 23: Frequency Facebook Use and Voter Turnout by Party



Notes: The red dashed line splits the data between voters and nonvoters. Data is from the 2012 election.

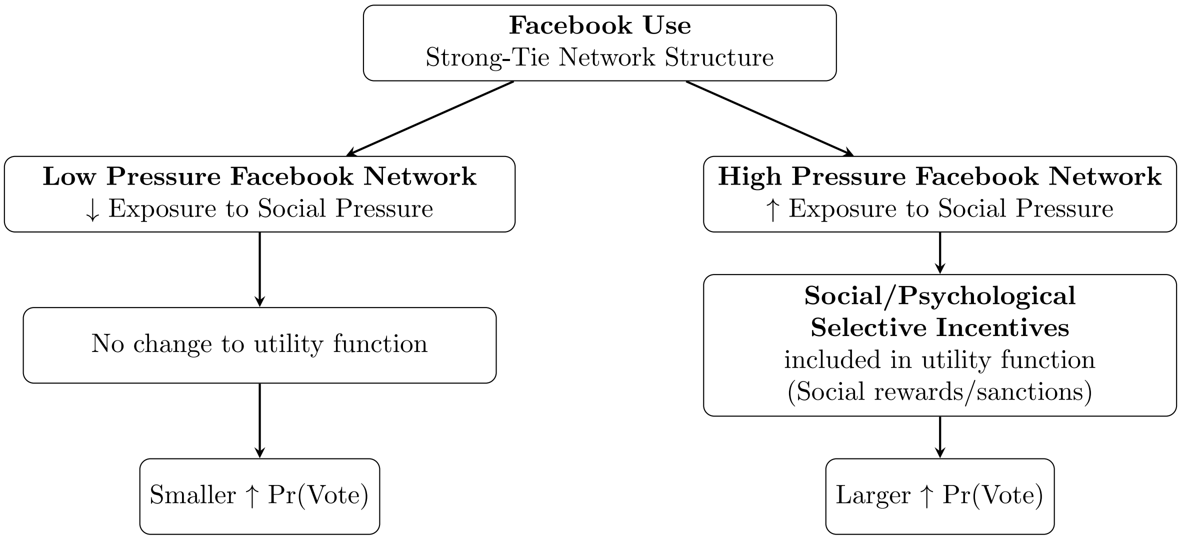
In 2012, election turnout was at 74% within the dataset, suggesting that participation during presidential elections is a social norm within the sample population (Table 3). Turnout dropped to 41% during the 2014 midterm election. This reduction in participation suggests that voting in the midterm election was not a strong social norm within the sample population. In the general population, the turnout rate for the eligible voting population was 36.7% (McDonald 2017).

Research suggests that turnout rates vary between presidential and midterm/off-year elections for a variety of reasons (Campbell 1987; Erikson 1988). Explanations include changes in the information environment and mobilization efforts, both formal and informal. Recent research into the social effects of election reform also speak to the differences in turnout between high information presidential elections and low information midterm and off-year elections. Voting methods such as "vote by mail" or "early voting" have resulted in reduced turnout in national elections. Researchers have attributed this difference to the reduced social interaction and visibility of election day activities necessary to mobilize voters (Burden et al. 2014; Thompson 2004). Though costs are reduced for some members of the community who vote regardless of the social environment, the overall reduction in formal and informal interaction leads to a decrease in turnout. Election Day Registration (EDR) reforms have resulted in increased turnout, providing evidence of the effect of social stimulation. EDR allows citizens to register and vote on the same day, preserving the social interaction and visibility available on election day. Midterm and off-year elections are low information and low visibility elections. Individuals are less likely to receive the stimulating effects from their community during low information elections. Due to the contextual differences that exist between these types of elections, the 2012 and 2014 elections are not directly comparable in this study. Regardless, they may provide useful insights into the influence of social network variables across election types.

Theory & Hypothesis

I theorize that Facebook use has a positive effect on individual turnout; the platform's network structure enables the user to receive social pressure, serving as an extrinsic motivator to vote. Social pressure from Facebook operates in addition to any motivators already present in an individual's face-to-face network. *The desire to belong to a social group and the desire to avoid social exclusion creates pressure to follow social norms.* The strong-tie network structure available on the Facebook platform advises members of social expectations, creating pressure to participate in socially approved behavior. The desire to maintain social status within the social group creates pressure to vote if that network indicates that voting is expected. Social pressure functions as a psychological selective incentive, an extrinsic motivator to vote. This provides a source of influence separate from reductions in information cost or intrinsic sources such as civic duty. The individual

Figure 24: Theory



will vote even if they are not interested in the traditional B term associated with casting a vote. These relationships are illustrated in Figure 24.

H1: Facebook Hypothesis

Facebook use increases the likelihood that an individual will vote.

Using Facebook exposes individuals to additional sources of social pressure and information than provided in their face-to-face networks.

H2: Social Pressure Hypothesis

Individuals who receive high levels of social pressure are more likely to vote than individuals who receive low levels of social pressure.

$Friends * Years$ measures the social pressure that is available to each user through their Facebook network. The effect of high social pressure networks ($Friends * Years =$ High Social Pressure score) on $Pr(Vote)$ will be greater than the effect of low social pressure networks ($Friends * Years =$ Low Social Pressure score). Including the product term in this model is essential as the measures work together to accurately evaluate social pressure received from a user's Facebook network. Individuals who have more Facebook Friends and have been members of Facebook for a longer period of time are considered to receive high levels of social pressure to follow social expectations from their Facebook network. These factors increase an individual's likelihood of voting compared to individuals who obtain low levels of social pressure through their Facebook networks. These individuals have less sources to receive social pressure from due to having fewer Facebook Friends and the short amount of time they have had a Facebook account.

H3: Large Network Hypothesis

Individuals with greater numbers of Facebook Friends are more likely to vote.

When social pressure is controlled for, the effects of nonsocial factors within the model are observed. Individuals with larger networks are exposed to a large amount political information from their network. This lowers the cost of political participation, increasing the likelihood of voting.

H4: Years of Membership Hypothesis

Individuals who have been members of Facebook for longer amounts of time are more likely to vote.

As in the Large Network Hypothesis, when social pressure is controlled for, the effects of nonsocial factors are observed. Individuals that have spent more time on Facebook are more likely to vote as they are more efficient at navigating and digesting the information, which lowers the cost of political participation.

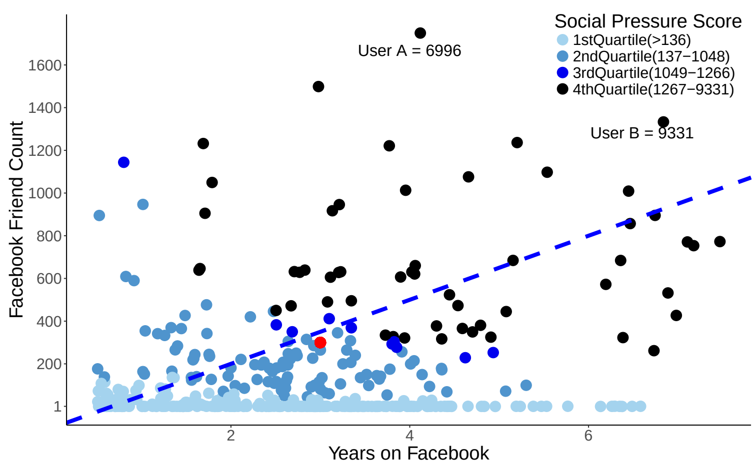
Measures & Model Estimation

Though the theory is non-interactive, an interactive model with a product term is used to assist in operationalizing the concept of social pressure within a Facebook network. The product term has two components, the number of Facebook Friends ($Friends$) that an individual user has and the number of years they have been a member of Facebook ($Years$). This approach draws on prior measures of online engagement present in the literature (Ellison, Steinfield, and Lampe 2007; Valenzuela, Park, and Kee 2009). Using both criteria ensures that the measure captures individuals who use Facebook as a strong-tie network through engaging in *interpersonal relationships* with other individuals.

As displayed in Figure 25, as the variable $Friends$ increases for most users, the variable $Years$ also increases. Individuals who are not utilizing the strong-tie network available on Facebook are users who 1) have high $Friends$ values, but are not using Facebook for a social purpose *or* 2) have high $Years$ values, but do not routinely access the platform to receive influence. These 'hybrid' users are not exposed to social pressure in the same way that traditional users of the platform are. This relationship is displayed in Quadrants II and IV of Figure 14. Incorrectly coding hybrid users as recipients of social pressure would introduce nonrandom error into the model. Using a multiplicative interaction between $Friends$ and $Years$ creates a new variable: The *Social Pressure Score*. Using a product term increases the score for individuals with high values for both $Friends$ and $Years$ but mutes the score for users who have a high value for only one variable. This score accounts for individuals who depart from the concept of social pressure. For example, a user with 300 Friends and one year on Facebook will receive a *Social Pressure Score* of 300, while a user with 300 Friends and three years on Facebook will receive a score of 900. Using a product term increases the validity of the measure of social pressure and eliminates bias from hybrid users.

$Friends$ against $Years$ are plotted to visualize the *Social Pressure Score* to ensure that these scores are behaving as intended, see Figure 25. The color gradient darkens as the *Social Pressure Score* increases. Dark blue and black points represent a high *Social Pressure Score*, where high levels of social pressure are received from a user's network. Light blue points indicate a low *Social Pressure Score*. User A with 1749 Facebook Friends received a *Social Pressure Score* of 6996. This value is lower than User B with 1333 Friends who received a score of 9331, the highest in the dataset. This outcome is due to the multiplicative interaction between $Friends$ and $Years$: User A had Facebook for four years, while User B had Facebook for seven years, increasing User B's score. The red point represents the average user in the sample with 300 Friends and three years on Facebook. The lowest *Social Pressure Score* was received by a user who had Facebook for two years with two Friends in their network. The social pressure measure appropriately reflects the levels of social pressure received from the user's network, depending on how they are using Facebook.

Figure 25: Friend Count and Years on Facebook Plot



Note: Data is from the 2012 election.

Individuals who adopted Facebook during an election year were coded as $Years$="1". This shows that these users had at least some interaction with their Facebook network, differentiating them from individuals who do not have a Facebook account. The Friend count of some users was not available. To avoid omitting these observations, they were coded as "2" Friends. This is the smallest network of any of the Facebook users; it indicates that the user was engaged with their network while providing a conservative estimate of the effect on Y. [31] The only social tie used for this measure is Facebook "Friends", not "Subscribers". Facebook "Friends" best represents a strong tie as the relationship is reciprocal. A user must accept a friend request from another user before they are considered Facebook Friends and join each other's network. "Subscribing" allows one user to view a second user's public posts, but that second user may not return the tie. Subscribers are not included in the measure as they represent weak ties. A user's Friend count provides information on the *amount* of social pressure received from a user's Facebook network. Users with more Friends receive more social pressure to follow group norms. This assumption is based on findings that indicate that social pressure is most effective when received through *multiple* members of an individual's network (Centola and Macy 2007; Centola 2010).

The log of $Friends$ is taken to allow the model to reflect the reality of social influence: After a certain number of Friends, additional connections are less likely to affect behavior.[32] Through the Facebook Newsfeed, users are exposed to social information in the form of posts by other users. A user must manually scroll through posts. A user with 50 Friends may see the same number of posts as a user with 100 Friends; the user with 100 Friends will receive more social pressure because they are exposed to social norms from a greater number of individuals. However, effects from the number of Facebook Friends in a user's network increases at a decreasing rate. As $Friends$ increases, the

[31] Additionally, as the log of $Friends$ is used in the analysis, it prevents $Friends * Years$ from equaling zero if "1" was used or -infinity if "0" were to be used, as these users would then be numerically indistinguishable from nonusers. Using a low, consistent value limits variation among the independent variables, biasing the model against finding an effect on Y. This approach avoids biasing the findings by imputing values. Given the small number of Facebook observations, there is not enough information to reliably impute data. The total number Facebook accounts discovered was 353, 160 of these are missing Friend Count values. Imputing missing values requires that data are missing completely at random (MCAR) or missing at random (MAR). These values cannot be assumed to be missing random as there may be an underlying reason why certain individuals would choose to limit public information. Providing a value of 1 controls for these observations while allowing the Years measure to impact the outcome. If Friend count = 0, the interaction would also have a value of zero, suppressing any impact from the Years variable, which is still measurable.

[32] The natural logarithm is used as a coefficient on the natural-log scale is interpreted directly: As x increases by 1, a coefficient of 0.01 can be interpreted to have a 1% increase in y (Gelman and Hill 2006).

likelihood that a user can view and receive influence from all members of their network diminishes.[33] Additionally, individuals are limited in the information they can synthesize at any one time (Simon 1979; Lau and Redlawsk 1997). A user's cognitive limitations minimize the effect of the Newsfeed. As a user scrolls through posts, there is a limited amount of information that they will be able to store in their short-term memories. Taking the log of $Friends$ recognizes the diminishing returns associated with increasing values.

There are two reasons behind employing a product term in the model versus using a non-interactive model and relying on compression provided by the logistic regression model. The Social Pressure measure is achieved by combining two partial indicators to produce a *single coefficient*. The *interaction* occurring between $Friends$ and $Years$ generates the measure of social pressure ($Friends * Years = Social\ Pressure$). A statistical test of the product term's coefficient appropriately evaluates the $Social\ Pressure$ measure. A non-interactive model is biased towards finding an interaction, falsely confirming the presence of a relationship between the two variables. This outcome is due to compression caused by the interactive nature of the logistical regression model.[34] A test of statistical significance cannot occur in a non-interactive model as it does not produce a coefficient representing the interaction. A interactive theory tested with a non-interactive model is not falsifiable as the model cannot represent situations inconsistent with the theory, i.e., the null hypothesis of no interaction (Rainey 2015). Using a product term avoids these issues by providing a coefficient that can be tested.

To determine the effect of social pressure on voter turnout, users who are recipients of *high levels of social pressure* to vote are compared to users who are recipients of *low levels of social pressure to vote*. Users with high values for both $Friends$ and $Years$ are considered recipients of high levels

[33] Additionally, the Facebook Newsfeed algorithm may further limit the variety of posts offered. The algorithm likely has an independent effect on social influence. This topic is not addressed in this paper. However, it is an essential phenomenon for future research to address.

[34] See Rainey 2015 for more information on the argument for using product terms in models were the interaction may be due to compression alone.

of social pressure. Social expectations are transferred from a greater number of individuals to the user; receiving social pressure from multiple sources is required to create change in behavior. The desire to maintain social group standing overcomes the costs associated with voting, preventing free riding. Individuals with low values for both $Friends$ and $Years$ receive low levels of social pressure. These smaller networks provide fewer sources of social pressure. In these networks, there is not enough social pressure to influence behavior and make voting a rational choice.

The 1st and 3rd quartiles of $Friends$ and $Years$ are compared to determine thresholds for individuals receiving high levels and low levels of social pressure. Users who have 400 Friends and have been on Facebook for 4 years (3rd quartiles) will receive high levels of social pressure. Individuals who receive low levels of social pressure are those with a friend network of 50 people who have been members of Facebook for 2 years (1st quartile). Comparing users across these thresholds allows for the observation of differences between the levels of exposure to social pressure present on Facebook.

The model accommodates a test for the effects of information transmission available on this platform. This measure models the overall effect of having a Facebook account, comparing users with nonusers. Once the interaction term is incorporated to account for social influence, the dichotomous variable representing the presence of a Facebook account will contain the effect of political information on turnout. Comparing this variable's effect when modeled with and without controlling for social pressure allows us to determine what factors, social and non-social, are influencing individual turnout.

Model Estimation

The dependent variable, $Pr(Vote)$ is a dichotomous measure of individual voter turnout in the 2012 General Election. $FacebookUse$ is a dichotomous variable representing whether the individual had a publicly accessible Facebook account before the 2012 or 2014 General Election. $Log(Friends)$ and $Years$ are the constituent elements used in the product term (Brambor, Clark, and Golder 2006). $Log(Friends)$ is the natural log of the number of Facebook Friends in an individual's Facebook network as listed on their public user profile. $Years$ represents how many years that a user's Facebook Timeline reported that they had a Facebook account. $Log(Friends)$ and $Years$ will allow us to test the Network Size and Years of Membership Hypothesis, respectively. The product term, $log(Friends)$ * $Years$, allows us to test the Social Pressure Hypothesis, determining the effect of social pressure on $Pr(Vote)$.[35] Including the product term changes the marginal effect of $log(Friends)$ on $Pr(Vote)$ (Ai and Norton 2003). $Log(Friends)$ is now dependent not only its own coefficient, but the coefficient of the product term and the value of $Years$.[36] The control variables consist of an individual respondent's age, gender, Party ID and fixed effects controlling for the individual's county of residence. Voter ethnicity was only reported for two of the four counties and is excluded from the current analysis.

Three models are used to estimate the effects of social pressure.[37] Model 1 estimates the effect of

[35] To determine the effect of the interaction, take the cross partial derivative of the expected value of Y (Ai and Norton 2003). Fr represents $log(Friends)$, Yr represents $Years$:
$\frac{\partial E(Y)}{\partial Fr \partial Yr} = [\beta_{Fr*Yr}] + [(\beta_{Fr} + \beta_{Fr*Y} Yrs)(\beta_{Yr} + \beta_{Fr*Yr} Fr)]$

[36] In a logit model, the marginal effect of x_1 on Pr(Y) depends on the values of all other independent variables. The marginal effect of x_1 is greatest when Pr(Y) = 0.5 and declines when pr Pr(Y) moves toward 0 or 1, due to a change in the value(s) of the variables in the model (Berry, DeMeritt, and Esarey 2010). To determine the instantaneous (marginal) effect of x_1 when all other variables are held constant at a set of values, take the derivative with respect x_1. The marginal effect of the number of Facebook Friends on the probability of voting:
$\frac{\partial E(Y)}{\partial F} = \beta_F + \beta_{F*Yr} Yr$
The marginal effect of x_1 on on Pr(Y) will vary linearly with x_2 when 1) all values of x_1 are held constant and 2)the product term is included. In the absence of a product term, the marginal effect of x_1 is β_1. Even in this instance, the marginal effect of x_1 on Pr(Y) still depends on the values at which the other independent variables were set.

[37]

$$Model1 : Pr(Vote) = logit^{-1}(\beta_0 + \beta_{FB} FacebookUse + \beta_A Age + \beta_F Female + \beta_{PID} PartyID + \beta_S State + \varepsilon_i \quad (4)$$

$$\begin{aligned} Model2 : Pr(Vote) = logit^{-1}(\beta_0 + \beta_{FB} FacebookUse + \beta_F log(Friends) + \beta_{Yr} Years + \beta_A Age + \beta_F Female \\ + \beta_{PID} PartyID + \beta_S State + \varepsilon_i \end{aligned} \quad (5)$$

Facebook Use only to determine the *collective* effect this platform has on turnout, including both social and non-social factors that may be present. Model 2 estimates the effect of $log(Friends)$ and $Years$ without the interaction term included. The output of Model 2 will be compared to that of Model 3, which correctly controls for social pressure. Model 3 includes the social pressure interaction variable, $log(Friends) * Years$. Models 4-6, which use the 2014 Midterm Election data, can be found in Table 14, Appendix 5. Models 2 and 3 are ran on a subset of the data that excludes individuals who are not Facebook users. This ensures that the analysis focuses on the difference in variation of social pressure *on Facebook*. To provide a robustness check, Models 2 and 3 will also be tested on the full dataset, available in Table 12, Appendix 4.

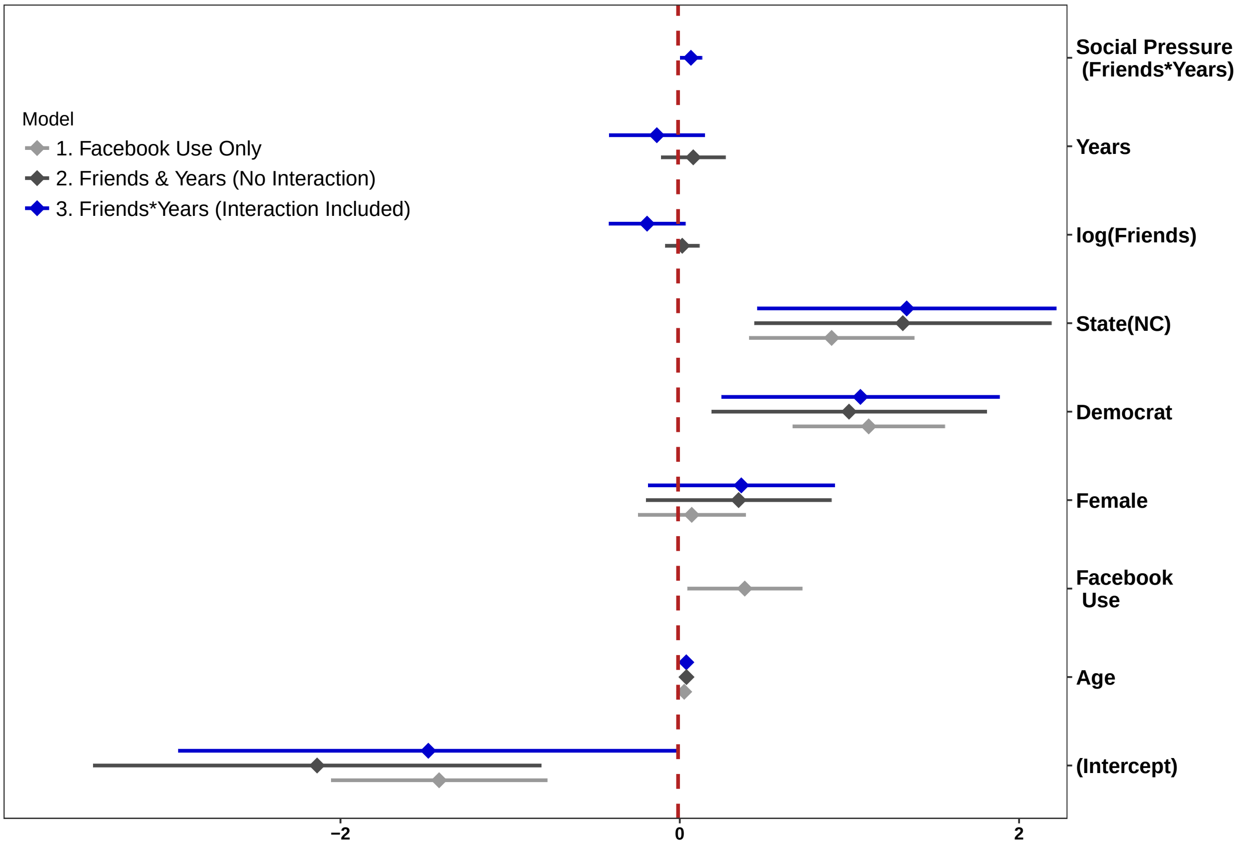
Results

This paper determines the effect of social pressure to vote, transmitted to individuals via Facebook's social network, on the probability that an individual will vote. Figure 26 displays the results of the logistic regression analysis. A complete table of regression estimates can be found in Table 11 and Table 12, Appendix 4.

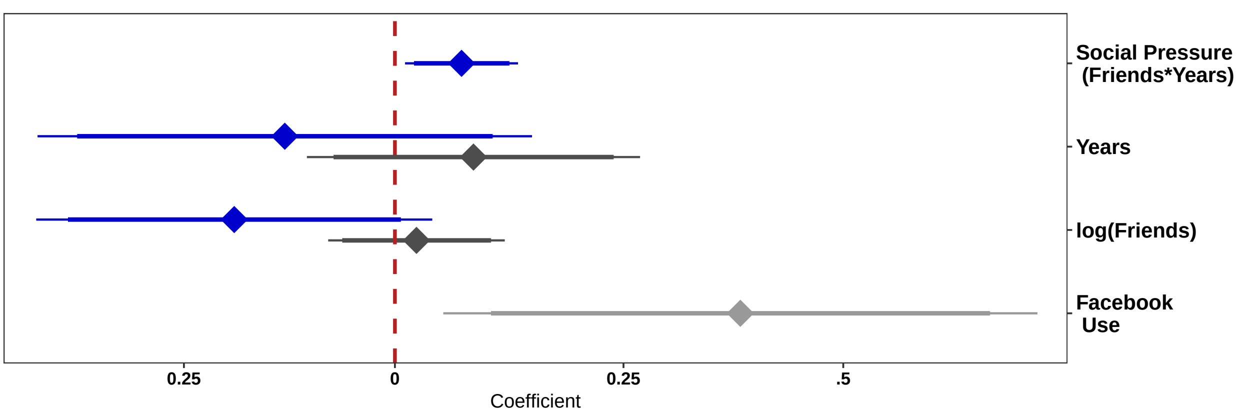
Model 1 estimates the impact of Facebook Use on $Pr(Vote)$ (Figure 26). Model 1 is non-interactive, supplying the *average* effect of Facebook on $Pr(Vote)$. General Facebook use has a positive and significant effect on $Pr(Vote)$, providing evidence for the Facebook Hypothesis: *Facebook use increases the likelihood that an individual will vote.* Model 2 estimates the effect of $log(Friends)$ and $Years$ without the interaction term included. The variable measuring the general effects of Facebook use drops from Models 2 and 3, as $Facebook\ Use$=1 in all cases. As

$$\begin{aligned} Model3: Pr(Vote) = logit^{-1}(\beta_0 + \beta_{FB}FacebookUse + \beta_F log(Friends) + \beta_{Yr}Years + \beta_{F*Yr}log(Friends)* \\ Years + \beta_A Age + \beta_F Female + \beta_{PID}PartyID + \beta_S State + \varepsilon_i \end{aligned} \tag{6}$$

Figure 26: Logistic Regression Estimates



(a) Full Coefficient Plot



(b) Partial Coefficient Plot: Main Independent Variables

Model 1: N= 908; Models 2 & 3 N=352. Points are logistic regression coefficients with standard error bars (95% =thick bar, 90% = thin bar. Data Source: Facebook.com, Miami-Dade Elections Department, Oklahoma State Election Board, Wake County Board of Elections, Erie County Board of Elections

both *Facebook Use* and *Years* measure the presence of a Facebook account, the general effects of Facebook use can be interpreted through *Years* in Models 2 and 3. These variables are highly collinear, see Table 13 in Appendix 4. Neither $Years$ or $log(Friends)$ is significant in Models 2 and 3; no support for the Large Network Hypothesis (*Individuals with greater numbers of Facebook Friends are more likely to vote*) or the Years of Membership Hypothesis: *Individuals who have been members of Facebook for longer amounts of time are more likely to vote.* Both of these hypotheses focus on the effects of general Facebook use, specifically lowering the cost of political information, not social factors.

$Years$ and $log(Friends)$ behave differently in Models 2 and 3. Both are constituent terms, which capture the effect of an increase in one of the variables, X, on the probability of voting when the other variable, Z, is zero. A sign switch is observed when the interaction is included. Both coefficients for $log(Friends)$ and $Years$ become negative after the interaction term removes the social effects of Facebook. The lack of support for the Large Network Hypothesis or the Years of Membership Hypothesis illustrates the importance of using interaction terms to better control for social vs. non-social effects. The effects of the non-social components in this model seem to be capturing a different causal process.

Model 3 includes the product term $log(Friends)$ x $Years$ (Figure 26). The product term's coefficient is significant and positive, providing preliminary evidence for the Social Pressure Hypothesis: *Individuals who receive high levels of social pressure more likely to vote than individuals who receive low levels of social pressure.* Though this coefficient is not directly interpretable, it is used to estimate the probabilities that will test the Social Pressure Hypothesis (Ai and Norton 2003). To ensure the analysis is based on the *variation* in social pressure available on Facebook, only individuals with a Facebook account are used in Models 2 and 3. Nonusers within the dataset are omitted from this portion of the analysis as they did not receive influence from a Facebook network. To check the robustness of the findings, Model 3 is applied to the full dataset in Table 12, Appendix 4. This analysis ensures that the effect of Facebook's social network still holds when the behavior of voters who do not use Facebook are incorporated.[38] A significant, positive effect on turnout is observed in Table 12. The Social Pressure Hypothesis remains supported when using full dataset.

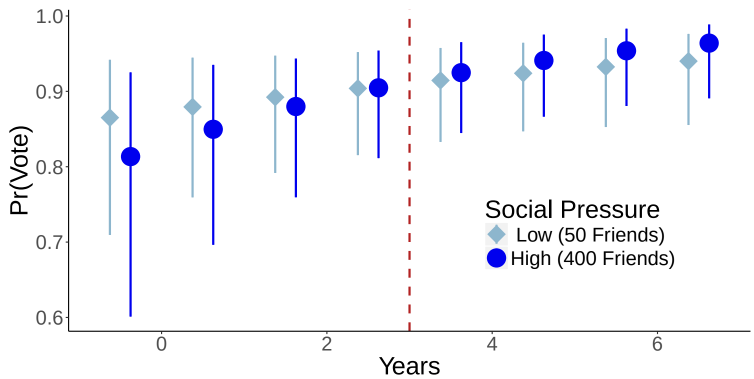
The effect of general Facebook use changes drastically between Models 1 and 3 (Figure 26). Model 1's estimates provide evidence that having a Facebook account produces a significant and positive effect on voting. This variable represents the total impact that Facebook has on turnout, including influence from both social and informational components. $Facebook\ Use$ drops from Models 2 and 3 as $Facebook\ Use$=1 across all observations. Due to collinearity with $Years$, the effect of $Years$ is used to gauge the impact of general Facebook use (see Table 13). When the interaction is introduced, the social impact is removed from the constituent terms. The representation of general Facebook, found in $Years$, becomes negative and is not statistically significant. Having an account alone does not contribute to an increase in the probability of voting, but instead probability depends on the social nature of Facebook use.

To interpret the substantive effects of these results, predicted probabilities are calculated. Figure 27 presents the probability that an individual will vote given the size of their Facebook network and the number of years they had a Facebook account. As theorized, an increase in social pressure within a user's network, represented by an increase in network size and years spent on Facebook, increases the probability that the user will vote. The $Years$ values range from "zero" years (nonusers) to seven years of Facebook membership. For ease of interpretation, Figure 27 focuses on networks of

[38] Users without a Facebook account are coded as $log(Friends)$=0 and $Years$=0 instead of omitting them from the analysis. The omission of non-users reduces the sample size to 341 observations. While this sample size is not ideal due to bias encountered with using MLE within small samples (estimates are biased away from zero), severe bias is found in samples of less than 50-100 observations (Firth 1993; Rainey and McCaskey 2015; Schoonbroodt 2002). A bias of 5% to 10% from sample sizes of 450 and 220 observations, respectively (Schoonbroodt 2002). Though this sample's size is not "critically small", it would benefit from an analysis using a penalized maximum likelihood estimator (PML) to reduce possible inflation of the estimates.

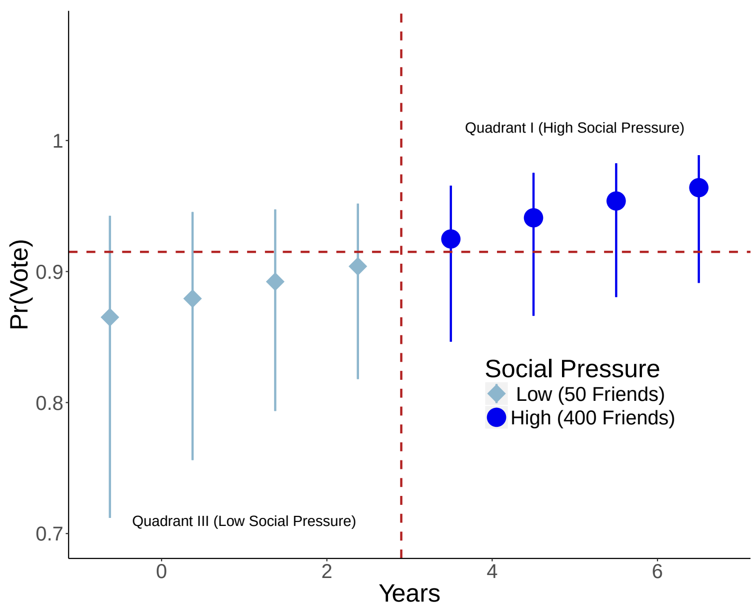
50 and 400 Friends, the first and third quartiles of *Friends* in the dataset.[39]

Figure 27: An Individual's Probability of Voting, Conditional on Facebook Network Size(Friends)



Points are predicted probabilities with simulated 95% confidence intervals, generated from logistic regression coefficient estimates.

Figure 28: Low Pressure and High Pressure Networks: Predicted Probabilities



The red dashed lines replicate the Quadrants depicted in Figure 14. Points are predicted probabilities with simulated 95% confidence intervals, generated from logistic regression coefficient estimates.

Recipients of high social pressure are users with large friend counts who have spent more years on Facebook, depicted as the dark blue points to the right of the red dashed line in Figure 27.[40]

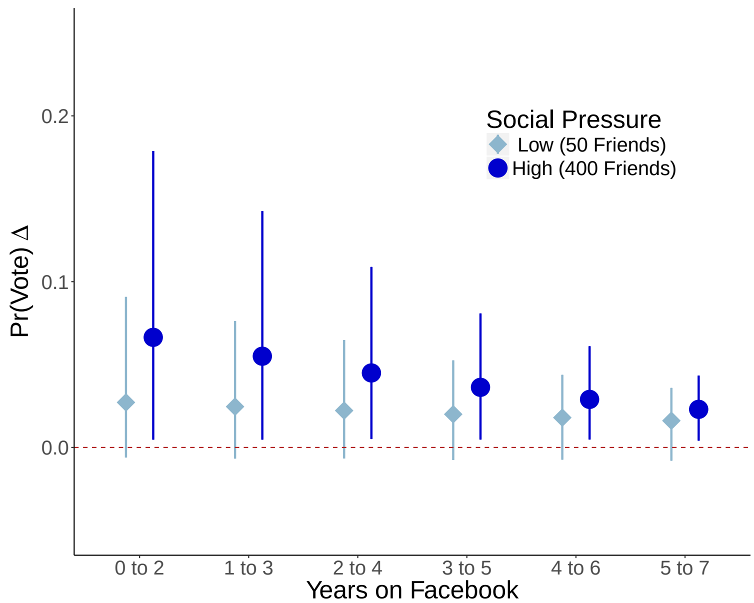
[39] Figure 45 in Appendix 4 includes predicted probabilities for networks ranging from "zero friends"(nonusers) to large networks consisting of 600 Friends. The probabilities are generated using *Age* at 35 years, as more variation in social media use is found within younger age groups (Figure 20). These effects are also present when the mean age in the sample is used (49 years old). Figure 46 in Appendix 4 plots probabilities for this age group.

[40] The placement of this line is arbitrary, it is meant to visualize a boundary between high and low social pressure networks.

The probability of turnout for a user in a network of 400 Friends at seven years on Facebook is 89%, compared to 85% in a smaller network of 50 Friends at the same time point. That is a 4% difference in turnout due to exposure to social pressure. Though this effect may seem small, elections are often won by a small margin. Increase in turnout by a few percentage points can greatly impact the outcome of an election in a close race. The patterns in the data replicate the trends found in Quadrants I and III of Figure 14. Users in Quadrant I (the upper right corner) have high Friend counts and more years spent on Facebook, and have therefore received high levels of exposure to social pressure. Quadrant III users (the lower left corner) have low Friend counts and have spent fewer years on Facebook, and have therefore received low levels of exposure to social pressure. The data are imposed upon the framework by incorporating the probabilities generated from logistic regression coefficient estimates, presented in Figure 28. The framework has the anticipated effect on voter turnout: the highest probabilities of voting are found within the *high social pressure networks*, represented by the dark blue points to the right of the dashed line. *Low social pressure networks*, represented by the light blue points to the left of the red dashed line, are associated with a lower probability of voting.

First differences are estimated to test that the probability of voting observed between two time points is *significantly different*. In Figure 29, the points display the change in $Pr(Vote)$ as $Years$ increases in two unit increments. First differences are calculated for both large (400 Friend) and small (50 Friend) networks across $Years$. Within the large network, the probability that a user will vote increases by 6% as $Years$ increases from zero to two years. This effect remains significant across all $Years$ values for the large network: the difference between the probabilities observed in Figure 27 is statistically significant. Though the $Pr(Vote)$ increases over $Years$ (Figure 27), this occurs at a decreasing rate. The *change* in $Pr(Vote)$ decreases as $Years$ increases; moving from five to seven years on Facebook has a smaller impact on the probability of voting (a 2% increase) than moving from zero to two years of use. In small networks, the change in the probability that an individual will vote as $Years$ increases is not statistically significant. The difference between the probabilities observed in Figure 27 is not significantly significant. These findings provide preliminary evidence for the Social Pressure Hypothesis: *Individuals who are recipients of high levels of social pressure are more likely to vote than individuals who receive low levels of social pressure.*

Figure 29: Change in $Pr(Vote)$ Between Years, Conditional on Facebook Network Size

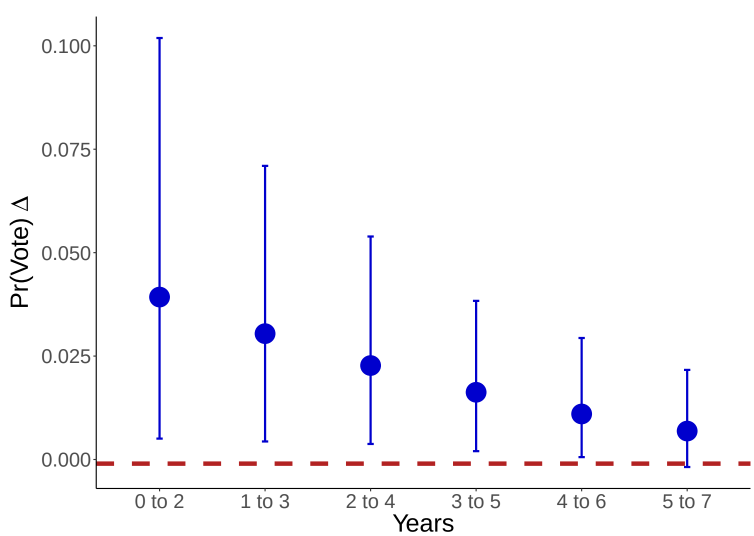


Points are estimated first differences with simulated 95% confidence intervals, generated from logistic regression coefficient estimates.

Second differences are then estimated to determine if the differences observed between high and low social pressure networks in Figure 29 are statistically significant. Figure 30 displays these results. A significant difference in the probability of voting occurs between the large and small network pairs in Figure 29. These findings provide further support for the Exposure to Social Pressure Hypothesis. The change in the probability of voting in a large network as $Years$ increases from zero to two is 3.9% higher than for users in a small network over the same time period. The second differences in Figure 30 remain significant up to the 4-6 year category. At 5-7 years, there is no significant difference in the likelihood of voting between high and low social pressure groups. This finding results from fewer observations being available at these points; only 11% of the Facebook users in the dataset had an account for five years or more (see Figure 25). Figure 30 illustrates that there is a significant difference in the predicted probabilities found in Figure 27, except for the points occurring after five years. This effect on $Pr(Vote)$ has decreasing marginal returns; there is less of a change in $Pr(Vote)$ between high and low social pressure networks at 4-6 years than at 0-2 years.

To fully test the Social Pressure Hypothesis, a significant difference must be found between points occurring in a high social pressure network (Quadrant I) and a low social pressure network (Quadrant III, see Figure 28). The strongest support for the Social Pressure Hypothesis is present in the data point at 2-4 years in Figure 30. Most of the Facebook users in the sample have had an account for less than five years; looking at the change between two and four years is therefore a realistic comparison for the dataset. This point is statistically significant, showing that there is a *significant difference* in the change in probability occurring between 1) the large and small networks and between 2) two and four years on Facebook.

Figure 30: The Change in $Pr(Vote)$ Between Users of a Small Network and a Large Network, as Years of Facebook Membership Increases



Points are estimated first differences with simulated 95% confidence intervals, generated from logistic regression coefficient estimates.

The logistic regression output for 2014 General Election can be found in Table 14 in Appendix 5.

The results of the 2014 General Election do not support any of the stated hypothesis. This finding is not surprising due to the lack of social pressure to vote during these elections. The comparison of the 2012 General Election (Models 1-3) and the 2014 Midterm election (Models 4-6) offers an opportunity to view outcomes when social pressure is applied and when it is absent. Midterm and off-year elections are low information and low visibility, and much election day socialization that mobilizes voting is lacking from these elections. Voting in mid-term and off-year elections is not considered a social norm, which is evident in the typically low turnout rates accompanying these types of elections. Social pressure is only applied to encourage behavior in compliance with social norms. When society does not direct actions towards a particular behavior, individuals will not receive rewards or punishments associated with the behavior. In this case, there is no social pressure serving as an extrinsic motivator. Individuals who vote in these elections are doing so not because of extrinsic motivation, but intrinsic factors.

Conclusion and Discussion

This paper provides evidence that online social networks influence voting behavior at the individual level. The strong- tie network structure available on Facebook allows the platform to transmit social pressure to follow social norms. Social pressure maintains compliance with established group norms. Increased exposure to the social pressure available on Facebook increases the likelihood that a user will vote. This effect supplements other causal processes. It does not replace the social pressure one may receive in offline networks but offers an additional source of influence. It also works alongside mechanisms increasing participation through the platform's ability to supply low-cost political information. This paper examines how the *network structure* of social media platforms contributes to behavioral outcomes. Facebook's network structure supports strong ties between individuals; this characteristic suggests that Facebook influences behavior through a different causal process than social media platforms that focus on political information transmission, such as Twitter. The strong-tie network structure of Facebook allows users receive social cues via their online social networks, informing users of the values of their social network. Individuals who are not interested in electoral outcomes or intrinsic motivators such as civic duty will choose to free ride. Social pressure serves as an extrinsic, social incentive to participate in collective action, overcoming the free rider problem. Social pressure changes the cost/benefit analysis associated with collective action. The addition of extrinsic incentives to rational choice models, such as the calculus of voting model, improves the prediction potential of these models.

Two causal mechanisms that explain the relationship between social media use and political behavior are 1) exposure to political information and 2) social pressure to follow group norms. Both of these theories alter the cost/benefit analysis associated with participation. Exposure to political information through social media platforms reduces the costs associated with participation. Decreases in costs essential to collective action, such as gathering information and coordinating behavior, influence individuals who are *already interested* in participating. Social influence provides a new incentive structure, changing the benefit received from voting from the electoral outcome to a social outcome, maintaining social status. Applying social incentives encourages behavior from those not interested in participating for the sake of voting itself, reducing free-riding.

Updating the calculus of voting model to include social incentives in the utility function allows for the model to predict turnout, a failure in earlier versions of the model. The benefit of voting is low and cannot overcome the costs within the model. The calculus of voting model relies on intrinsic motivators such as civic duty, which ties the benefit of voting to the act itself. According to rational choice theory, rational actors should choose to abstain. However, researchers observe millions of individuals turning out to vote, and the traditional calculus of voting model fails to predict the empirical reality. Introducing extrinsic, social motivators into the model overcomes this problem.

Social pressure offers social rewards for following norms and social sanctions for deviating from this behavior. Social norms are communicated through political discussion within social networks. Social rewards include increased inclusion or improved social status, while social sanctions include exclusion and a decrease in social status. Social media platforms can apply *virtual* rewards and penalties. Facebook's social rewards involve accumulating Friends, likes, tags, shares, and positive comments. Social punishments include receiving negative comments and reductions in Facebook Friends, likes, tags, shares, and positive comments received. The social nature of humans and their desire for inclusion in face-to-face and virtual networks drives the motivation to follow social norms; the benefit of voting is not tied to the act of voting itself. The addition of social pressure in the calculus of voting model alters the utility function, making participation a rational choice. These findings speak to the general importance of including social factors into models of political behavior. The individual decision-making process cannot be considered in isolation from social influences.

By utilizing the social network available through Facebook, researchers can better understand the effect of the transmission of social norms occurring between members of a social group. Research finds that the networks available on Facebook replicate face-to-face networks. This characteristic provides support that the social pressure present in traditional networks is also present within the social networks of Facebook. Facebook Friend networks are an accumulation of small, primary networks "collected" over time. The Facebook platform lowers the cost of maintaining relationships with members of past face-to-face networks, maintaining a strong-tie relationship. Facebook's strong-tie network structure enables the platform to transmit information on social norms, including the norm of voting. Members of our sample are registered voters with a high probability of voting; this property of the sample supports the assumption that voting is a social norm in these networks and that social pressure to vote is present.

This paper builds on prior measures used in social media analysis. Surveys surrounding social media use have helped flesh out causal processes and determine valid measures of social media use. This study adds to the research by applying these measures to a new dataset. Using publicly available social media data to create datasets is becoming increasingly attractive to researchers. Using measures refined by prior studies to assess a user's engagement with their online network ensures that our measure correctly captures the impact of social pressure on individual users. A dichotomous measure of social media use comparing Facebook users against nonusers is not appropriate. It is necessary to examine the levels of social pressure within the Facebook users in the sample to determine how Facebook influences voter behavior.

To measure the influence of social pressure within Facebook networks, the model analyzes the *variation in social pressure received* through the platform. The effect of Social Pressure is measured by the product term's coefficient. The product term consists of a user's Facebook Friend count and the number of years they have been a member of the Facebook platform. A large network can transmit more social pressure as users receive social cues from a greater number of sources (network members). To change behavior, receiving social signals from multiple sources is necessary. Additionally, individuals who have been members of Facebook for many years are habitual users who have incorporated Facebook use into their day-to-day lives. These users receive more exposure to the social norms present in their network. In both cases, these individuals are exposed to more instances of social pressure to vote. Though the theory is not interactive, the data require an interaction between these measures to appropriately operationalize Social Pressure. Using both of these variables reduces bias from individuals who are not using Facebook as a strong-tie platform. For example, individuals who have only recently acquired an account but quickly developed an extensive online network lack strong ties to their Facebook network. These individuals will not receive information on social norms; their inclusion pollutes the measure of social pressure. The interaction term reduces the impact of this user's high friend count as the variable measuring years will be low, lowering the overall Social Pressure score. This process prevents the user from being coded as a member of a high social pressure network.

As theorized, individuals who are exposed to high levels of social pressure are more likely to vote. The probability of voting found in high social pressure networks is *significantly different* than the probability of voting for users in low social pressure networks. Users with low levels of exposure to social pressure are less likely to vote. As the social pressure within a user's network increases, represented by increases in network size and years spent on Facebook, the probability that they will vote also increases. The importance of social media analysis extends beyond the platform's ability to lower the information costs associated with participation. These findings also extend beyond Facebook use; they can apply to any platform with a strong-tie network structure. The ability of social media networks to supply social pressure offers another source of prediction and explanation of political behavior.

This study enables researchers to increase our understanding of *why* changes in communication technology have the effect they do on political outcomes. A social network perspective explains behavior through a different causal process than models based on changes to information costs. Social processes influence political behavior differently than information-based models and may lead to more insights into behavioral outcomes. For example, the impact of social media on political polarization of the electorate may benefit from the application of social perspectives. Current narratives state that social media may lead to the creation of political echo chambers, where ideologically homogeneous groups share reinforcing ideas (Chadwick and Howard 2009; Prior 2007; Iyengar and Hahn 2009). Explanations for this phenomenon primarily focus on selective exposure. Critics of selective exposure highlight that individuals are not as hostile to and dismissive of information counter to their ideology as required by selective exposure explanations (Kinder 2003; Chaffee et al. 2001; Zaller 1992). Additionally, if selective exposure does occur, it is most likely among politically sophisticated individuals only (Graber 1984). If individuals are not engaging in selective exposure due to individual-level factors, adopting a social network perspective may assist in explaining the phenomenon of selective exposure. An individual's online network resembles their homogenous, face-to-face network. The desire for social inclusion may cause individuals to appeal to the ideological norms of that group. This process limits the diversity of information available within these networks and encourages preference falsification, perpetuating ideological homogeneity and contributing to greater ideological polarization.

4 THE CONSEQUENCES OF DIGITAL SOCIALIZATION: EXAMINING THE EFFECT OF AGE COHORT NORMS AND FACEBOOK USE ON VOTER TURNOUT

Abstract

A social media user's age dictates their level of "digital socialization", and this impacts the extent that a social media platform can influence a user's behavior. I theorize that Facebook use has a unique effect on voter turnout within the youngest voting eligible cohort (18-25 years of age) compared to the "Typical User" cohort above 25 years of age. Users receive online social pressure due to the strong-tie network structure of Facebook, which serves as a selective incentive to vote. The "Young User" cohort is more receptive to online social pressure due to high levels of digital socialization. The data for this study was collected by matching Facebook user profiles to voter registration lists from four U.S. counties. Facebook use is found to have a significantly different effect on the turnout of young users compared to older users. Within the Young User cohort, the probability of voting increased by 57% as exposure to online social pressure increased. Within the Typical User cohort, increasing online social pressure lead to a decrease in turnout by 3%. These findings have broad implications for the future of democratic citizenship in the face of rapidly changing communication technologies. To understand the behavior of the next generation of voters and communicate effectively with them, researchers, activists, and political leaders will need to understand the depth and intensity of their relationship to social media.

Introduction

Trends in both political participation and social media use among young voters raise two questions for the future of democracy: how does social media use impact political participation among young users today, *and* how will social media impact political participation as young users age and replace the current dominant voting bloc? To address the first question, traditionally, young people are less likely to participate in politics for a variety of reasons. Political elites put more effort into mobilizing older voters (Rosenstone and Hansen 1993). Older citizens are attractive to campaigns as they are more likely to vote and have stronger connections to the community, while young individuals may feel disconnected from candidates who tailor their messages to older citizens. Campaigns that focus on youth mobilization experience a surge in the youth vote (Leighley and Nagler 2014). This provides evidence that when candidates appeal to their needs, young citizens are willing to vote. The effect of institutional impediments to voting is also greater for young citizens and first-time voters. Reductions in registration costs are found to have a large, positive effect on young voters, providing evidence that young people do want to participate but are dissuaded by high costs (Leighley and Nagler 2014). Online opportunities reduce mobilization and participation costs for both candidates and citizens (Mossberger and Tolbert 2010; Chadwick and Howard 2009; Margetts et al. 2015; Xenos, Vromen, and Loader 2014; Margetts 2001; Evans, Cordova, and Sipole 2014; Hemphill and Roback 2014; Margetts et al. 2015). The ability of communication technologies to reduce the costs of engagement has a positive effect on youth turnout and political participation.

The second point concerns the future of democracy as a result of increased reliance on digital communication technologies. Some theorists fear cultural decline from the loss of face-to-face communication (Mutz and Young 2011; Putnam, Leonardi, and Nanetti. 1993). Counter to this argument, digital communication has been shown to strengthen interpersonal connections and increase political participation (Mutz and Young 2011). Research on digital communication technologies and engagement support the second argument, particularly among young citizens.[41] The variety of variables and causal mechanisms explored allows researchers, policymakers, and advocates to better understand the future of democracy in the digital age. As present generations are replaced by technologically oriented generations, the effects of digital socialization will have a greater impact on politics. This can be seen already through party change and the adoption of online campaign tactics (Margetts 2001). By exploring how a strong-tie social media platform influences participation among young citizens compared to older citizens, this paper contributes to research on democratic citizenship and engagement.

[41] See: Kittilson and Dalton 2010; Dalton 2008; Dalton and Kittilson 2012; Xenos, Vromen, and Loader 2014; Chadwick and Howard 2009; Mossberger and Tolbert 2010; Valenzuela, Arriagada, and Scherman 2014; Bimber 2001; Bimber 2003; Boulianne 2011; Ellison, Steinfield, and Lampe 2007; Farrell 2012; Gibson and McAllister 2013; Gibson 2015; Lev-On and Hardin 2008; Margetts et al. 2015; Nisbet and Scheufele 2002; Valenzuela, Park, and Kee 2009. These works are discussed in more detail throughout this paper.

Digital Socialization

The proliferation of social media use has spurred research into its effect on political participation. However, the impact of technology on participation has raised issues of digital inequality regarding internet access (Brundidge and Rice 2010; Mossberger and Tolbert 2010). As internet access becomes increasingly global, the question shifts to how *user characteristics* impact technology's effect on political behavior. This calls for a greater focus on the effects of technology *between* those who are already online. This paper focuses on age cohorts, investigating how socialization to digital communication technologies, or "digital socialization", influences political behavior.

Like other behaviors, social media use is influenced by the socialization process. Socialization introduces individuals to norms and standards regarding behavior and interaction of the society to which they belong (Genner and Süss 2017). Agents of socialization include family members, peers, school, work, religious affiliation, the media and the political climate. The socialization process varies across generations, resulting in unique behavioral traits present within each generation. For example, children and young adults in the 1960's and 1970s were socialized into accepting protest as a legitimate form of political action (Harris and Gillion 2010). This process is evident in the increased rates of protest for this age cohort across time, compared to other cohorts.

The analysis compares users who received high levels of digital socialization, the "Young User" cohort, to individuals who received low or no digital socialization in their childhood, referred to as the "Typical User" cohort. The Young User cohort contains individuals between 18 and 25 years old, while the Typical Use contains all users above 25 years of age. Technology often defines generations, and a defining mark of the Millennial generation is the widespread use of rapidly evolving communication technologies. The Millennial generation contains those born between 1981 and 1996 (Dimock 2018). In 2006, when the youngest Millennials were coming of age, social media use was on the rise. At this time, Facebook was already a popular platform: Facebook had been available to those with university email accounts since 2004. Norms surrounding social media use and interaction with communication technologies were developing and socializing the members of the Young User cohort, even if members were too young to have a social media account at the time. 41% of Millennials surveyed in 2006 had at least one social media account, while less than 6% of older age groups had an account (Pew 2018a). This trend establishes that social media use was becoming a norm for young people. In 2012, 88% of Millennials surveyed had at least one social media account. Social media use was less universal among older cohorts; 68% of 30-49-year-olds had a social media account in 2012, compared to 48% of 50-64-year-olds.

The digital socialization that Millennials received separates them from previous generations, but also leads to variation *within* Millennials. 18-25-year-olds represent the *youngest* Millennials in the sample. The older Millennials in the sample were between 26 and 31 years of age in 2012. Older Millennials experienced many technological changes within their childhood, but reached adulthood before social media use was widespread. During the formative years of *younger* Millennials, communication technology was considerably more advanced then it was during the childhoods of older Millennials. Specifically, young Millennials were exposed to social media use, as all members of this age this group were younger than 20 years old at the time of Facebook's public release in 2006. Segregating generations based on their relationship with technology is not a new phenomenon: popular media defines "Xennials" as a micro-generation composed of people born between 1977 and 1983 (Merriam-Webster 2018). Xennials bridge Generation X and the Millennial generation, claiming that their socialization process does not allow them to fit easily into either generation. As this study is concerned with how online social pressure impacts age cohorts at different rates, it is essential to define cohort members based on their digital socialization, rather than rigid age guidelines such as decades or generations.

Social media use within younger generations has continued to increase into 2017, providing evidence that digital socialization is an enduring issue. The new group of "young users" includes both older members of Generation Z and the last of the Millennials. Generation Z, or post-Millennials, include those born in the mid-1990's to mid-2000's (Dimock 2018). This group uses an average of four platforms and engages with these platforms with greater frequency than older users (Smith and Monica, Anderson 2018). Additionally, 51% of young users state that social media would be hard to give up, compared to 40% of all social media users. Use of messaging apps is high among young users compared to all other age groups (Greenwood, Perrin, and Duggan 2016). These apps are focused on interpersonal communication, signifying that they possess a strong-tie network structure. Though social media use has increased in popularity among all cohorts, the norms of use among young citizens offer evidence of digital socialization.

Research tends to assume that citizens of all ages are "equally affected by influences on their electoral decisions" (Franklin and Weber 2010). Models fail to take into account age-related heterogeneity, ignoring the differences that occur between older generations with fixed habits and younger generations whose behavior is malleable (Wessels et al. 2004; Franklin and Weber 2010). There is a reason to believe that age does have an important effect on behavior. For example, when generalizing the findings of experiments performed on college students to an entire population, researchers often point out that the college-age population is too different from the general population for findings to apply (Fridkin and Kenney 2010). Additionally, the literature has considered differences between levels of socioeconomic status, political interest, and political knowledge. These differences are found to have unique effects on political behavior (Zaller 1992; Brady, Verba, and Schlozman 1995; Lau and Redlawsk 1997). Allowing the independent effects from different political generations to interact appropriately with variables of interest improves the prediction of turnout models (Franklin and Weber 2010). This approach predicts that the greatest change should occur among younger citizens, as older members of the electorate are established in their political behavior and less likely to be influenced. When considering the impact of social media on voter turnout, age becomes a crucial factor due to the relationship that age cohorts have with communication technology.

The relationship between age-related processes and turnout illustrates the importance of incorporating age effects into models of voting behavior. Young people are less likely to vote compared to older citizens (Campbell et al. 1960; Wolfinger and Rosenstone. 1980; Leighley and Nagler 2014). Turnout for 18-29-year-olds was 45% in 2012, while all other age groups voted at rates of 60% or higher (Census Bureau 2012). Though age is related to other predictors of turnout, including income and education, age functions independently and serves as a proxy for life experiences (Wolfinger and Rosenstone. 1980; Rosenstone and Hansen 1993). Age-related processes include forming civic skills and gaining political knowledge, which reduces the cost associated with participation (Brady, Verba, and Schlozman 1995). These processes also include social elements, such as the establishment of residency and development of community affiliations, which have a positive effect on turnout (Strate et al. 1989; Abrams, Iversen, and Soskice 2011; Gerber, Green, and Larimer 2008).

Network Structure & Social Pressure

This paper utilizes a rational choice framework that incorporates social pressure as a social/psychological selective incentive into the utility function (Gerber, Green, and Larimer 2008). Social pressure encompasses the process of social learning, diffusion of social information, and social constraint (Balbo and Mills 2011). The homophilic nature of social networks guides the social behavior of their members (McPherson, Smith-Lovin, and Cook 2001; Abrams, Iversen, and Soskice 2011). Social pressure offers social rewards for following group norms and threatens those who resist with social sanctions (Abrams, Iversen, and Soskice 2011; Gerber, Green, and Larimer 2008; Gerber, Green, and Larimer 2010a; Green and Gerber 2010; Cialdini and Goldstein 2004; Panagopoulos 2010; Mann 2010; Gerber, Green, and Larimer 2010b; Davenport et al. 2010). Social pressure to follow group norms serves as an extrinsic motivator. Network members provide social pressure and are willing to monitor and sanction the behavior of others (Ostrom 1998; Ostrom 2000). Social pressure encourages participation when the barrier to collective action is free riding: the motivation to act stems not from the collective benefit received, but on social rewards and the avoidance of social sanctions.

In the traditional calculus of voting model, a citizen will vote if $p(B) + D > C$ (Downs 1957; Riker and Ordeshook 1968). Citizens are motivated to vote by the benefit received from the electoral outcome (B), and deterred by costs associated with voting (C). D represents intrinsic incentives received from the act of voting, such as engaging in one's "civic duty" (Riker and Ordeshook 1968). As the probability of being pivotal (p) is near zero in an election with millions of voters, $p(B) + D$ cannot overcome C, and abstaining is the dominant strategy (Riker and Ordeshook 1968; Feddersen 2004). Abstainers will still receive the benefit without incurring any of the costs associated with collective action. Rational actors should abstain (free ride), yet millions of citizens choose to vote, introducing the "paradox of voting"(Downs 1957). Evidence shows that individuals behave strategically when deciding to vote (Wolfinger and Rosenstone. 1980; Gimpel and Dyck 2005; Blais 2000). This finding indicates not that citizens are irrational, but that the model is missing a key element of individual decision making. Theories that rely on intrinsic motivations as explanatory variables, such as expressive benefits received regardless of the outcome or civic duty, do not answer the not answer the underlying question of *why* a citizen values participation (Barry 1970; Aldrich 1993; Feddersen 2004). Social pressure theories of voting complement existing approaches that focus on intrinsic motivators or cost/ benefit analysis. Social pressure offers an extrinsic incentive to participate to those who are not motivated by reductions in costs or intrinsic benefits

Social pressure theories posit that the utility from voting stems from social rewards and sanctions (Feddersen 2004; Gerber, Green, and Larimer 2008; Abrams, Iversen, and Soskice 2011).

Turnout models should involve extrinsic motivators, which offer a stronger explanation for turnout than intrinsic incentives alone (Harbaugh 1996). Citizens are informed of the importance of an election through political discussion within their social network (Abrams, Iversen, and Soskice 2011). Members of a group are pressured to follow social norms to receive social approval as a reward and to avoid social disapproval from disregarding the norm (Gerber, Green, and Larimer 2008; Abrams, Iversen, and Soskice 2011). For example, an individual may be rewarded with more respect or through inclusion in more social group activities. Social sanctions are administered by the social group; they involve being excluded from social group activities or losing the respect of others (Ostrom 2000). Social pressure theories propose a modification to the traditional calculus of voting model that includes both intrinsic and extrinsic motivations to vote (Aldrich 1993; Blais 2000; Feddersen 2004; Gerber, Green, and Larimer 2008; Abrams, Iversen, and Soskice 2011). An individual will vote if $p(B) + D_I + D_E > C$. D_I represents intrinsic motivators, such as civic duty or expressive benefits. Extrinsic factors, D_E, embody the social aspect of voting, specifically social pressure. These variables are found to be the strongest predictors in the model (Gerber, Green, and Larimer 2008). With the addition of D_E, voting becomes the dominant strategy.[42]

Social norms regarding participation are communicated through social interaction (Abrams, Iversen, and Soskice 2011; Putnam, Leonardi, and Nanetti. 1993). The characteristics of Facebook's network structures that enable this platform to provide social pressure: Facebook is a social media platform composed of *strong ties* between individuals. The strength of strong ties hypothesis addresses the tie structure found in this social media platform (Valenzuela, Arriagada, and Scherman 2014). Strong ties support the transmission of complex social concepts and are necessary to produce changes in behavior (Centola and Macy 2007; Centola 2010; Valenzuela, Arriagada, and Scherman 2014). Previous research finds that an individual's Facebook Friends consist of the same

[42] A game tree illustrating this process is available in Figures 54 and 55 in Appendix 7).

members found within their offline social groups, providing evidence that Facebook ties produce social pressure (Ellison, Steinfield, and Lampe 2007; Arnaboldi et al. 2012; Dunbar et al. 2015). Virtual networks that are not based on existing offline networks are not as effective in mobilizing participation (Gibson and McAllister 2013). The Facebook platform allows users to maintain virtual connections with members of past face-to-face networks at a low cost (Ellison, Steinfield, and Lampe 2007; Lev-On 2010). The relationship between social interaction and political participation also extends to online social interaction (Dalton and Kittilson 2012; Kittilson and Dalton 2010). Facebook offers a variety of features enabling users to interact with their network and receive information on social norms. Users receive social information through the Newsfeed feature. They can post and share information via their Timeline. Facebook users can post and receive comments or "likes" (see Chapter 2 for more details on this platform).

Contrary to the strong ties approach, the strength of weak ties hypothesis posits that weak-tie networks change behavior through their capacity to spread information rapidly across distant ties. Information undoubtedly influences the costs associated with participation. However, these effects are limited to individuals who are already interested in participating (Ostrom 2000). Strong-tie platforms are more efficient at *changing behavior in individuals otherwise not inclined to act* compared to weak-tie platforms. Free riding is reduced as participation does not rely on the collective benefit, but on social incentives to follow group norms.

Users join online social groups with the intention to connect with others. The uses and gratifications approach includes many goals associated with an individual's online activity, and interpersonal goals include maintaining social relationships and social status (Li 2011; Baumgartner and Morris 2010; Shah et al. 2005). Social status consists of the respect, influence, and prominence an individual maintains within their social group (Baumeister and Leary 1995; Anderson et al. 2001). Research has found that users value their social standing within the online community. Social media use has been found to impact self-worth, social standing and social attractiveness (Gonzales and Hancock 2011; Valkenburg, Peter, and Schouten 2006; Tong et al. 2008; Ellison, Heino, and Gibbs 2006). Online interaction can also influence offline behavior, including suicidal thoughts and actions (Hinduja and Patchin 2010). Despite negative experiences online, individuals feel pressure to stay connected with others to avoid feeling the "Fear of Missing Out," or FOMO (Przybylski et al. 2013). The importance that individuals attach to social media platforms allows the online network to influence behavior. Online social rewards and sanctions function like offline social rewards and sanctions. Users will engage in behavior that will result in social rewards such as increased likes, receiving positive comments, and maintaining/increasing their Friend count. They avoid behavior that could diminish their social status, including receiving negative comments or being "de-friended" by other users. Social media use is directly related to giving and receiving social influence to attain intangible, social rewards. These rewards and punishments provide social pressure to follow social norms, supplementing social pressure found in offline networks.

To influence behavior, it is necessary to receive social pressure through *multiple* members of an individual's network (Centola and Macy 2007; Centola 2010). Large networks transmit more "units" of social pressure to the Facebook User than small networks. Less populated networks have fewer ties, supplying less exposure to social pressure. Network size is easily measured on Facebook using the Friend count feature. The more Facebook Friends a user has, the more social pressure that user will receive from their online network. Advances in technology allow large groups to mimic small group effects by reducing the costs associated with monitoring behavior and applying rewards or punishments (Lupia and Sin 2003; Lev-On and Hardin 2008; Margetts et al. 2015; Olson 1965).

Figure 31: Facebook Use and Voter Turnout by Age

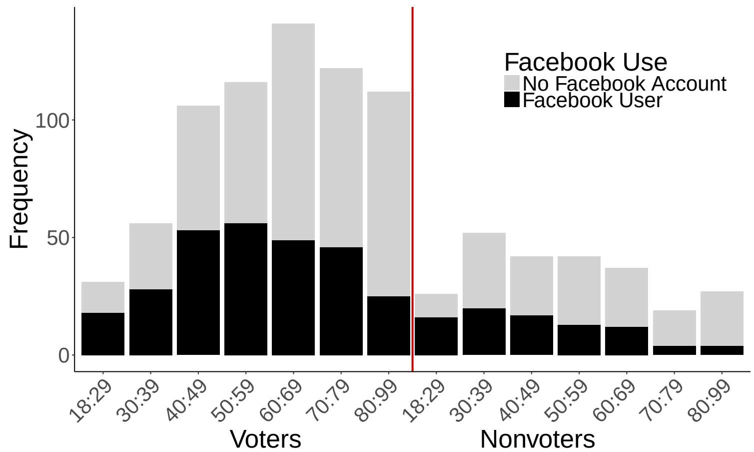


Figure 32: Friend count and Age Plot

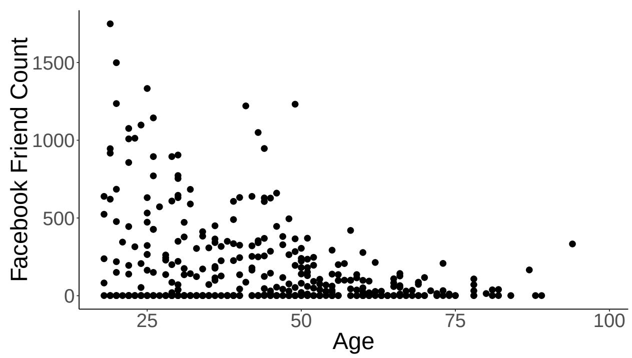


Figure 33: Years on Facebook and Age

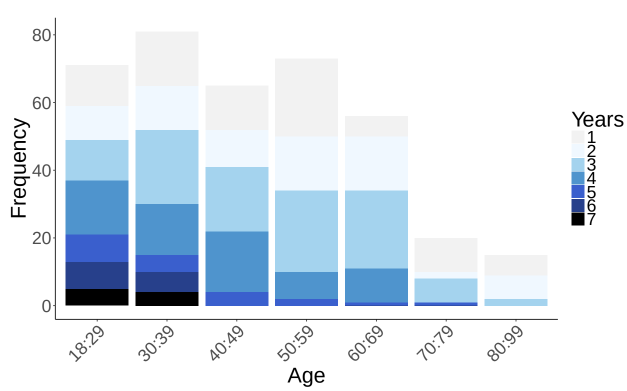
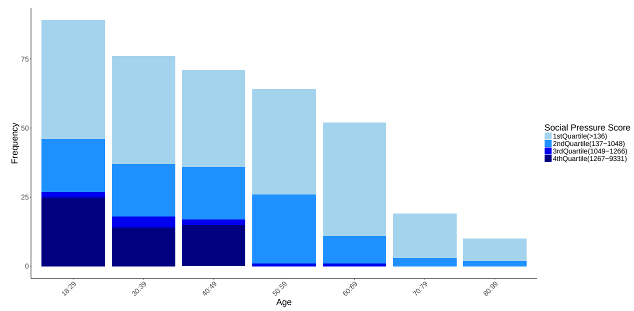


Figure 34: Social Pressure Score by Age



Social Pressure Score = Friends ∗ Years, see Measures section for more details

Data

This dataset consists of a random sample of 1,000 registered voters drawn from the voter registration rolls of four U.S. Counties: Wake County, North Carolina; Oklahoma County, Oklahoma; Miami-Dade County, Florida; and Erie County, Ohio. Using a sample of registered voters who already have a high probability of turnout provides a conservative estimate of Facebook's effect on turnout; any change observed in the dependent variable will provide strong evidence of the effect of Facebook use on voter turnout. This approach was necessary to verify individual turnout.

A list of verification criteria from the voter registration lists and the Facebook search engine were used to detect if voters had a publicly accessible Facebook account (more information on the data collection process is found in Chapter 2). Table 15 in Appendix 7 provides descriptive statistics for the dataset. 38% of the sample had a publicly available Facebook profile in 2012. The number of Facebook Friends and the year that the user adopted Facebook was recorded. After the 2012 election, voter registration lists were collected to incorporate the 2012 General Election results into the dataset.[43]

Figure 31 illustrates the relationship between Facebook use, age, and voter turnout.[44] Voter

[43] A 9% drop-off was observed from the pre-election to post-election sample of registered voters. Registered voters are removed from the rolls due to death, a felony conviction, changing residence, registering in another county, or lack of voter contact. The criteria for removal varies by county.

[44] The descriptive statistic figures categorize age groups by 10-year intervals, except the first group that includes 18 and 19-year-olds.

turnout increases with age, dropping off among the oldest voters (see Figure 47, Appendix 7). Facebook use is highest among young individuals, and use decreases with age (see Figure 51, Appendix 7). Voters tend to use Facebook at higher rates than nonvoters, with an exception for 18-29-year-olds, among whom social media use is the most prevalent. 18-29-year-old nonvoters used Facebook at slightly higher rates than 18-29-year-old voters.[45]

In 2012, the average user in our sample had 172 Facebook Friends and had spent almost three years on Facebook. Facebook Friend count and Years of Membership statistics across age groups are available in Appendix 7, Tables 16 and 17. Younger users had more Facebook Friends, see Figure 32 (also, Figure 49, Appendix 7). Facebook users 25 years old or younger had an average Facebook Friend count of 346, while users over 25 years of age had an average Friend count of 139. Younger users tended to have been a member of Facebook for a longer amount of time, see Figure 33. Users 25 years of age or younger had Facebook for and an average of 3.5 years, while users over 25 years of age had Facebook for 2.7 years.

The Social Pressure measure used in this paper is composed of Facebook Friend count and Years of Membership. The relationship between Facebook Friend count and Years of Membership is positive and linear for users within the dataset (see Figure 50, Appendix 7). Most Facebook users build their networks over many years; this finding is consistent with our concept of social pressure within a strong-tie network. The relationship between *Social Pressure Score* and age is illustrated in Figure 34.[46] A greater percentage of younger users (the rightmost bars within Figure 34) have high *Social Pressure Scores*, indicated by the dark blue portion of the bars. As age increases, the *Social Pressure Score* decreases. Older members of Facebook are exposed to networks with lower levels of social pressure, shown in the rightmost bars within Figure 34.

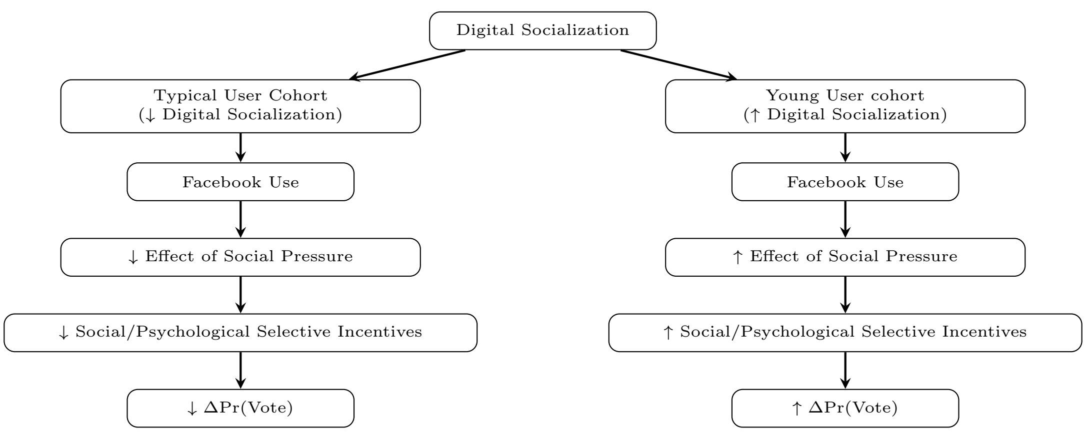
[45] Of the 18-29-year-old voters, 58% had a Facebook account. Of the 18-29-year-old nonvoters, 62% had a Facebook account.

[46] Figure 34 does not use the log of Facebook Friends (*Friends*) in order to correspond with the values used in Figure 50 in Appendix 7, which shows the Friend count value and their relationship to Years of Membership (*Years*). Note that the *Social Pressure Score* used in the analysis utilizes the logged value of *Friends*

Theory & Hypothesis

I theorize the effect of social pressure received through Facebook use varies in intensity and direction across age groups due to the level of digital socialization received by an individual. Facebook use has a unique effect on individual turnout for the younger users of Facebook compared to the older users. The platform's network structure enables the user to receive social pressure as an extrinsic incentive to participate in politics. However, digital socialization makes young age groups more sensitive to online social pressure. This relationship is illustrated in Figure 35. The impact of age on social media use and political participation is well-documented: while young individuals make up a majority of social media users, their involvement in politics tends to be lower than other age groups (Chadwick and Howard 2009). However, more research is needed to investigate the effect that the internet has on young users *compared to* the entire population. Without the inclusion of all age groups in a single study, we cannot determine if the effect of social media on political behavior is *significantly* different than other age groups.

Figure 35: Theory



This paper addresses differences in turnout based on age *and* online social pressure, allowing a comparison between age groups beyond just rates of social media use. Social media has unique effects on the behavior of different age cohorts due to their level of digital socialization. For young people, a greater portion of both their social interaction and political participation takes place online. The digital socialization that a citizen receives will impact the effect of social pressure exerted by social media platforms.

H1: Young User Effect Hypothesis:

Facebook users in the Young User cohort are less likely to turnout compared to Facebook users in the Typical User cohort.

Younger individuals use technology at higher rates than older users, reducing the information costs associated with voting. Though Young Users have the highest *Social Pressure Scores* (see Figure 34), I do not expect that the Young User cohort will *exceed* the participation rates of the Typical User cohort. Access to information alone is not enough to create a shift in voter turnout patterns.

The interaction between social media use and age controls for the rates of use across age cohorts in our sample. Once this is accounted for, the effects of social pressure to vote *within* each of these cohorts are comparable. This hypothesis is tested by examining the probabilities associated with the turnout rates for different age groups and then determining if the difference in Pr(Vote) between groups is significant.

H2: Magnitude of Effect Hypothesis:

Exposure to social pressure will cause a greater change in $Pr(Vote)$ for Facebook users in the Young User cohort than the Typical User cohort.

Young users are more likely to be influenced by Facebook use than older populations. Members of the Young User cohort are the greatest consumers of social media and show higher levels of attachment to this platform compared to older users. Young Users are socialized to use social media platforms to interact with others and participate politically. Social media platforms became available during the Young User cohort's formative years and have been integrated by these users, as evidenced by user statistics (Pew 2018b). The youngest user in the sample would have been 12 years old when Facebook was made available to the public.[47] Early adoption of the platform and the major role it plays in young peoples' lives increases their susceptibility and willingness to be influenced by online platforms. This hypothesis is tested by observing the difference in $Pr(Vote)$ between older and younger cohorts across different levels of social pressure. This hypothesis is tested by examining the change in the probability of voting for different age groups across levels of social pressure and determining if the change in $Pr(Vote)$ significant.

Direction of Influence Hypotheses

In addition to the magnitude of the effect of online social pressure, this study investigates the direction of the effect. I present two competing hypotheses as to whether Facebook use will decrease or increase $Pr(Vote)$. Each of the hypotheses investigates a pattern of behavior that may be present on social media. Both hypotheses address that the Young User cohort is traditionally disengaged and places less value on voting. In this cohort, social pressure to engage in alternative forms of participation is present, but social pressure to vote is not. The second hypothesis takes this a step further by applying a social capital approach to how exposure to online engagement and skill development may increase voter turnout. While social pressure to *vote* may not be available, following social capital theory, increased contentedness generates social capital, as well as engagement in alternative forms of participation. This process may have an indirect effect on turnout for the

[47]Note that the minimum age to use Facebook is 13 years old. Individuals under 13 still receive information from friends, family, and news/entertainment media regarding the platform's popularity.

Young User cohort.

H3: Negative Social Pressure Hypothesis:

Facebook users in the Young User cohort will experience a decrease in PR(Vote) as Social Pressure increases.

Young users are members of groups that typically do not value voting, evident in lower turnout rates both in the sample and in the general population. There are fewer social incentives offered in younger networks for voting and users also do not fear punishment for choosing not to participate. This hypothesis predicts that as individuals are exposed to others who do not value voting, they are less likely to vote. Young individuals place importance on "actualizing citizenship" norms rather than "dutiful citizenship norms" (Xenos, Vromen, and Loader 2014). A decrease in turnout is expected for the Young User cohort as members are exposed to norms encouraging other forms of participation *instead of voting*.

H4: Positive Social Pressure Hypothesis:

Facebook users in the Young User cohort will experience an increase in PR(Vote) as Social Pressure increases.

Though young users are members of groups that typically do not value voting, online participation is greater for young users compared to other age groups (Mossberger and Tolbert 2010). Participation *is* important for these groups: when presented with the opportunity to participate in a way that is accessible and meaningful to them, members of the Young User cohort have taken advantage of the opportunity. Virtual activity positively contributes to social capital formation and political participation (Kittilson and Dalton 2010; Baumgartner and Morris 2010; Valenzuela, Park, and Kee 2009; Margetts et al. 2015). Politically relevant social capital is produced by political information and expertise communicated within the network, encouraging political participation (Lake and Huckfeldt 1998). Social capital formation is a cyclical process: social capital produces political participation, which in turn produces more social capital. The Young User cohort may be exposed to increased pressure to engage in online forms of participation compared to what they would receive offline. As individuals receive pressure to participate in online forms of engagement they develop social capital, increasing the probability they will vote. In this case, voter turnout is a by-product of social pressure to engage in other forms of political participation.

Measures & Model Estimation

Age Measure

A dichotomous measure of age is used to separate individuals with high levels of digital socialization (18-25-year-olds) from other users, those above 25 years of age. A dichotomous measure was used instead of a continuous age variable to capture broadly applicable generational or micro-generational effects. Additionally, the small N available in this study offers a limited number of young users at some age points (see Figure 51, Appendix 7).

The Young User cohort experienced high digital socialization. The analysis compares these users to individuals who received low or no digital socialization in their childhood, referred to as the "Typical User" cohort. Looking further into this measure, Figure 36 visualizes the Social Pressure scores of the Young User cohort and the Typical Users, who serve as the "base" category for the dummy variable, the leftmost bar.[48] To illustrate the differences in Facebook use between the Young

[48]Figure 52 in Appendix 7 displays the number of observations within these two categories, separated by Facebook use. Though there are more observations for Typical Users, a greater proportion of the Young User cohort had a Facebook account and are recipients of high levels of social pressure

Figure 36: Social Pressure Score by Age (Two Categories)

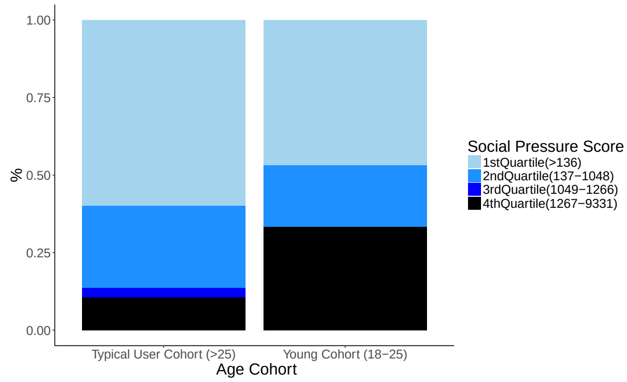
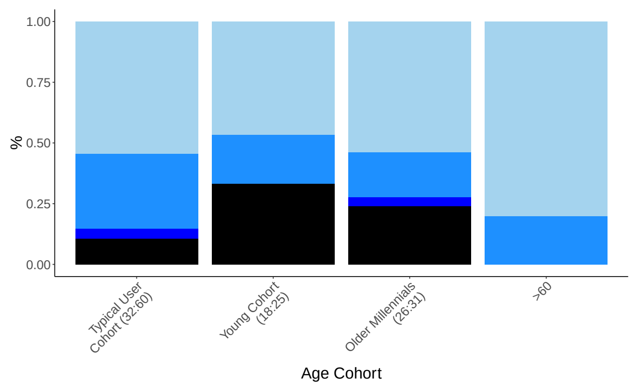


Figure 37: Social Pressure Score by Age (Four Categories)



User cohort (18-25 years of age) and older Millennials (26-31), Figure 37 shows the percentages of users in four different age categories.[49] The Young User cohort maintains the highest percentages of social pressure of all the age categories, even when compared to older Millennials (26-31-year-olds). A model using age as an ordinal variable with four categories is estimated to determine if there is a difference in the effect on Pr(Vote) between the Young User cohort, older Millennials, and the two oldest cohorts.[50]

[49] Figure 37 in in Appendix 7 provides the number of observations within these four categories, separated by Facebook use.

[50] Users older than 60 are separated from the Typical User cohort as senior members of the electorate tend not to have the same level of digital skills and have not been socialized into communication technologies the same way as those born in the latter half of the 20th century.

Social Pressure Measure

This paper uses a measure of Facebook that allows researchers to access the social aspects of social media use (detailed in Chapter 2). Prior studies tended to focus on a dichotomous measure of an individual's presence on Facebook, which allows researchers to target the effect of *general* Facebook use (Baumgartner and Morris 2010; Valenzuela, Arriagada, and Scherman 2014). However, this effect will include the information aspects of Facebook use as well as social factors, muddying the effects of either explanatory variable. In addition to the member's presence on Facebook, the measure employed in this study incorporates unique elements of each user's online social network: the Facebook Friend count and the number of years they have been a member of the Facebook platform. Past research has validated using Facebook Friend count as a measure of Facebook use (Valenzuela, Park, and Kee 2009). This provides increased variation in the independent variable

Content analysis approaches, such as text analysis of tweets or Facebook comments, enable researchers to analyze messages of social pressure directly. Though information on the independent variable(s) may be greater, the dependent variables available are limited. Without administering a survey, researchers are limited to political participation represented by that user's online activity, such as changes in the numbers or content of tweets and Facebook posts. To access other forms of engagement such as voting, a researcher is required to administer a survey. Though an excellent methodological tool, survey research also has challenges in this particular area of study, namely non-response bias and voter overreporting. Non-response bias is an issue with any survey but is compounded due to internet literacy (Atkeson 2010). Though Facebook users are assumed to have a minimal level of internet literacy as they have accessed the platform to set up an account, internet literacy varies across users. Online surveys are prone to nonresponse from those with lower internet skills, which tend to be those who are poor, older, less educated, African-American and Latino (Mossberger, Tolbert, and Stansbury 2003). This study's focus on age-related differences in social media use requires a method that bypasses the issue of nonresponse from older users. Using objective measures such as Friend count and Years of membership on Facebook allows researchers to target these individuals, improving inference. This study contributes to the growing literature using publicly available observational data from social media platforms to craft datasets without relying on survey methodology. Additionally, this approach gets around the issue of overreporting individual turnout (Silver, Anderson, and Abramson 1986). Matching voter records to Facebook profiles allows researchers to validate turnout.[51] If overreporting is due to social pressure to conform to social norms, relying on survey results may bias a study modeling effects of social pressure.

Using Friend count alone to measure social pressure is not sufficient; while most members of Facebook use the strong- tie network structure available, some users may seek other types of connections (Ugander et al. 2011). Users may employ the platform for non-traditional purposes, such as information gathering or distribution, which are characteristics of a weak-tie network. These users are not socially close to their network and will not receive social pressure through their connections. Facebook is used by these members as one would use a weak-tie platform such as Instagram or Twitter (Valenzuela, Arriagada, and Scherman 2014). For example, some "hybrid" users have amassed thousands of Facebook Friends but have only had their Facebook accounts for a year, indicating that they have not developed close social ties with their Facebook network. The Facebook networks of these users are not virtual manifestations of offline networks, Friends are added indiscriminately. Hybrid users are more interested in disseminating information, and they perceive their Friend count as a reflection of their social status. This phenomenon is similar to the desire to become "Instagram famous."[52] Using only the Facebook Friend count codes these users as

[51] Starting with Facebook profiles and matching them to voter registration records is technically possible, but not feasible given that voter registration lists are available at the state or county level if they are distributed by the state at all. The approach used in this paper first selects registered voters using voter registration lists that are available to the public. Though this approach is more likely to code an individual as not having a Facebook account incorrectly, it does not incorrectly code whether the individual is a registered voter and their turnout in each election.

[52] "Instagram famous," or "Insta-famous," refers to otherwise ordinary users who have reached microcelebrity status through their ability to accumulate thousands of followers (Marwick 2015).

recipients of high levels of online social pressure when they likely receive little social pressure from the platform. Using Frequency of Facebook use as a measure would also fail to differentiate between these two types of users; hybrid users are likely to have a high frequency of use score in an effort to maintain their public image. Measuring a user's level of intimate engagement with their Facebook network by incorporating the years of Facebook membership discounts the effect of members who are not using Facebook as a strong-tie network.

Social Pressure and Age Interaction Term

The product term coefficient, $Friends * Years * Age$, determines if an interaction exists between online social pressure and age cohort, and the effect of this interaction on $Pr(Vote)$. Using an interaction term to determine this relationship is necessary due to the effects of compression found in logistic regression models which will bias the model towards confirming a false interaction (Rainey 2015). The interaction term will provide a coefficient necessary to test the hypotheses.

I utilize a three-way interaction between $Friends$, $Years$, and Age. This approach is taken instead of collapsing $Friends*Years$ into a single measure of "$Social\ Pressure$", then using an interaction term composed of $Social\ Pressure*Age$ to test for the relationship between online social pressure and age. This approach is also possible as the Social Pressure interaction composed of $Friends*Years$ functions in a predictable manner: the relationship is linear and positive. However, a three-way interaction offers more control over the values of the variables within the interaction. For example, the product of the mean of $log(Friends)$, 3.19, and $Years$, 2.8, is 8.9, while the mean of $log(Friends) * Years$ is 9.5. Additionally, the mean of $log(Friends) * Years$ as a single measure may not represent average values within the dataset. For example, "9.5" could also represent a user with a $log(Friends)$ value of 9.5 and a $Years$ value of 1, which is not representative of an average user.

The interaction effect includes the product term's coefficient as well as the coefficients and values for each constituent term.[53] Additionally, including the product term changes the marginal effect of Age on $Pr(Vote)$ (Ai and Norton 2003; Francoeur 2011).[54]

Model Estimation

The dependent variable, $Pr(Vote)$ is a dichotomous measure of individual voter turnout in the 2012 General Election. $Friends$, $Years$, and Age are the constituent elements used in the product term (Brambor, Clark, and Golder 2006). $Friends$ is the natural log of the number of Facebook Friends in an individual's Facebook network as listed on their public user profile. $Years$ represents how many years that a user's Facebook Timeline reported that they had a Facebook account. $Friends$ and $Years$ will allow us to test the effect of $Social\ Pressure$ on $Pr(Vote)$. Age is a dichotomous variable measuring the effect of the youngest Facebook users in the dataset, 18-25-year-olds, against the base group, those above 25 years of age. $Friends$ * $Years$ * Age is a three-way interaction, producing the product term that will allow a test for interaction between online social pressure and age.

$Facebook\ Use$ is a dichotomous variable representing whether the individual had a publicly

[53] To determine the effect of the three-way interaction, we take three derivatives with respect to x_1, x_2, and x_3: (Norton, Wang, and Ai 2004). Fr represents $log(Friends)$, Yr represents $Years$, Age represents $Age = 18:25$:

$$\frac{\partial E(Y)}{\partial Fr \partial Yr \partial Age} = [\beta_{Fr*Yr*Age}]+[(\beta_{Fr} + \beta_{Fr*Y*Age} Yrs * Age)(\beta_{Yr} + \beta_{Fr*Yr*Age} Fr * Age)(\beta_{Age} + \beta_{Fr*Yr*Age} Fr * Years)]$$

[54] Age becomes dependent not only its own coefficient but on the value of $Years$, $Friends$, $Friends$*$Years$, and the coefficients of $Friends$*$Years$*Age, $Friends$*Age, and $Years$*Age. In a logit model, the *marginal effect* of x_1 on Pr(Y) depends on the values of all other independent variables. The marginal effect of x_1 is greatest when Pr(Y) = 0.5 and declines when pr Pr(Y) moves toward 0 or 1, due to a change in the value(s) of the variables in the model (Berry, DeMeritt, and Esarey 2010). To determine the instantaneous (marginal) effect of x_1 when all other variables are held constant at a set of values, take the derivative with respect x_1.

The marginal effect of Age on the probability of voting (Francoeur 2011):

$$\frac{\partial E(Y)}{\partial Age} = (\beta_{Age} + \beta_{AgeYr} Yr) + (\beta_{AgeFr} + \beta_{AgeFrYr} Yr)Fr$$

Fr= Facebook friends and Yr = Years, Age represents Age=18:25

The marginal effect of x_1 on on Pr(Y) will vary linearly with x_2 when 1) all values of x_1 are held constant and 2) the product term is included. In the absence of a product term, the marginal effect of x_1 is β_1. Even in this instance, the marginal effect of x_1 on Pr(Y) depends on the values at which the other independent variables are set.

accessible Facebook account before the 2012 General Election. This variable is used in Models 4 and 5; Models 1-3 are run only on Facebook Users. The control variables consist of an individual respondent's gender, Party ID and fixed effects controlling for the individual's county of residence. Voter ethnicity was only reported for two of the four counties and is excluded from the current analysis.

Three models are used to estimate the effects of social pressure.[55] Model 1 estimates the effect of the interaction occurring between *Social Pressure* ($Friends * Years$) and *Age*. Though this is a three-way interaction, *Social Pressure* is a single concept, ranging from zero to 50.4 units. In Model 1, the base age is set to that of the Typical User to allow us to determine how the youngest age cohort (18-25 years of age) behaves in comparison. In Model 2, Millennials are divided into two cohorts. Additionally, voters above 60 years old are separated from Typical Users. These separations capture variation in digital socialization. In Model 3, age is continuous. Models 1-3 are tested Facebook users only as the goal is to investigate the effects of social media use across age cohorts. Excluding nonusers allows the model to look at the difference in the effect of social pressure among individuals who have self-selected onto this platform. According to the uses and gratifications approach, users have selected into social influence, making users conceptually different from nonusers. Models 4 and 5 in Appendix 7 use the full dataset.

[55]Models 1, 2 and 3 are represented by Equation 7. In Model 1, Age 18:25=1; Age>25 =0. In Model 2, Age 18:25=1; 26:31=2; 32:60=0 Age>60 =3. In Model 3: Age = continuous value between 18 and 99.

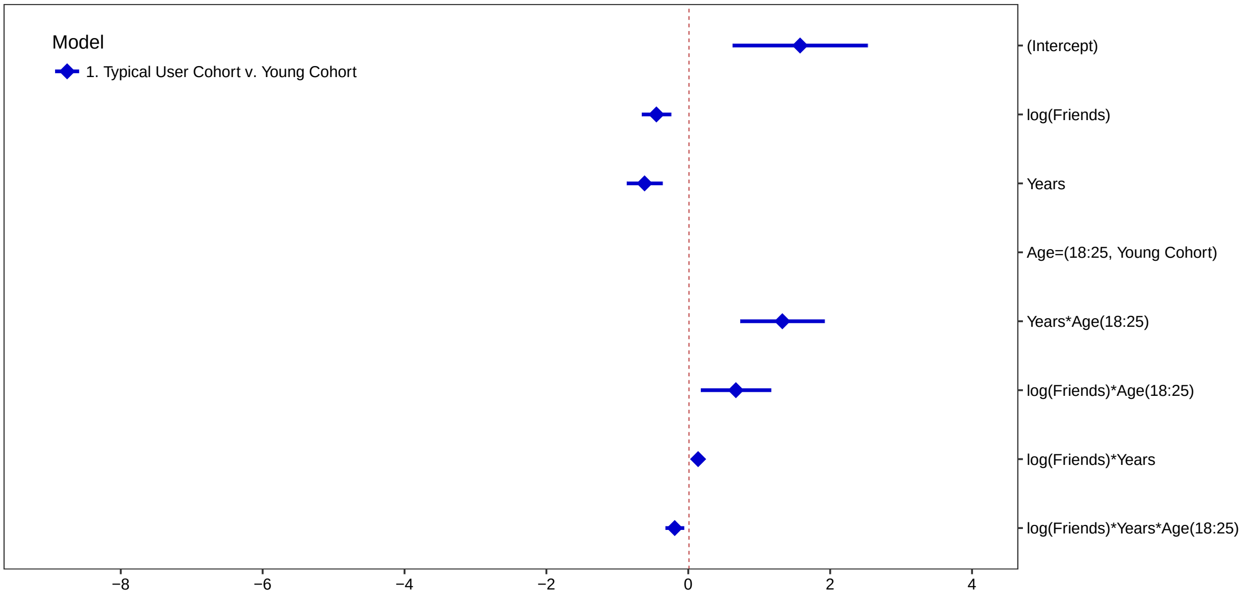
$$\begin{aligned} Pr(Vote) = logit^{-1}(\beta_0 + \beta_A Age + \beta_{Fr} Friends + \beta_{Yr} Years + \\ \beta_{A*Fr} Age * Friends + \beta_{A*Yr} Age * Years + \beta_{Fr*Yr} * Friends * Years + \\ \beta_{A*Fr*Yr} Age * Friends * Years + \beta_F Female + \beta_R Republican + \beta_S State : OH + \varepsilon_i \end{aligned} \tag{7}$$

In Model 4 (Equation 9) and Model 5(Equation 10), Age 18:25=1; Age>25 =0.

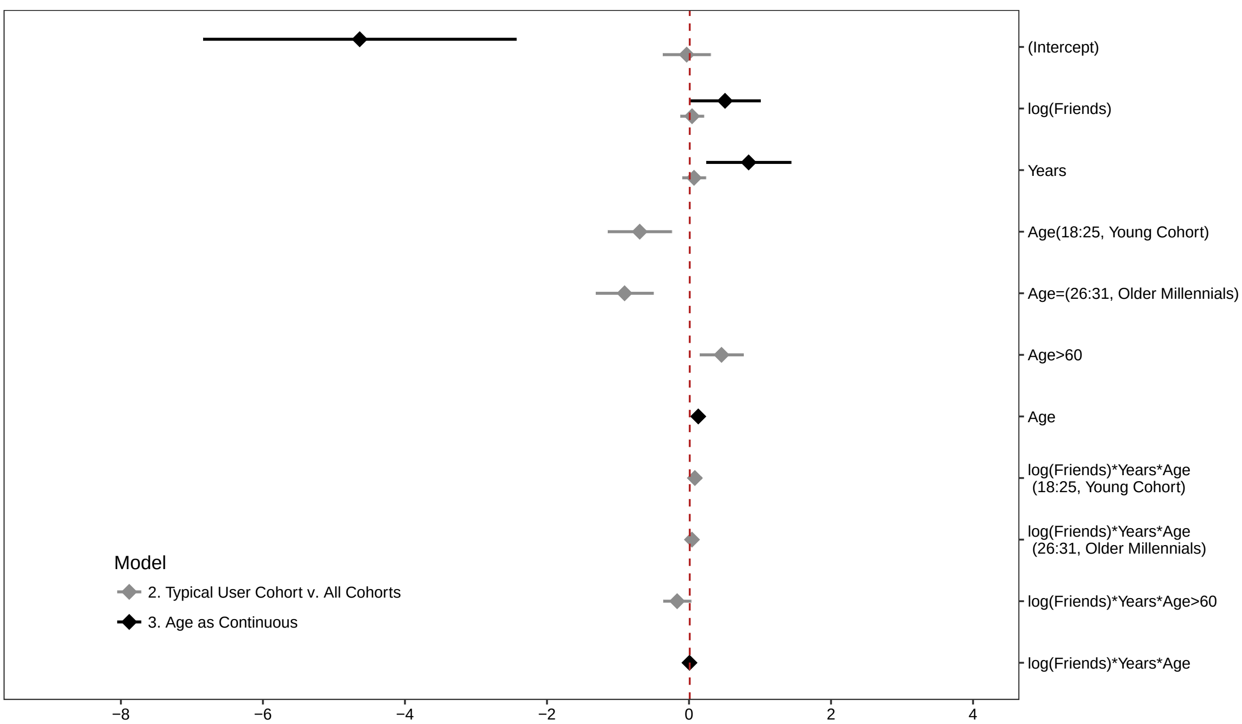
Results

This paper determines the relationship between social media use and age, and what effect this relationship has on the probability of voting. The results of the logistic regression analysis are shown in Figure 38. A complete table of regression estimates is found in Table 18, Appendix 8. Figure 38(a) provides estimates for Model 1: the three-way interaction between the Social Pressure measures ($Friends$ and $Years$) and the dichotomous age variable. The Young User cohort consists of the 18-25 year-olds in the sample and the Typical User cohort is composed of members of the sample over 25 years of age. The interaction coefficient is significant and negative. This finding provides preliminary support for the Young User Effect Hypothesis: Facebook users in the Young User cohort are less likely to vote compared to Facebook users in the Typical User cohort. Model 2 provides estimates for four age cohorts, see Figure 38(b). In Model 2, the interaction coefficient with Young Users ($log(Friends) * Years * Age$=18:25) is significant, providing further support for the Young User Effect Hypothesis. No significant change is observed between the Typical User cohort, Older Millennials (26-31) or those over age 60. Young Millennials who received high levels of digital socialization exhibit different behaviors than users who did not receive high levels of digital socialization, including older Millennials. This shows that the difference is not just generational, but based on socialization to social media platforms.

Figure 38: Logistic Regression Estimates



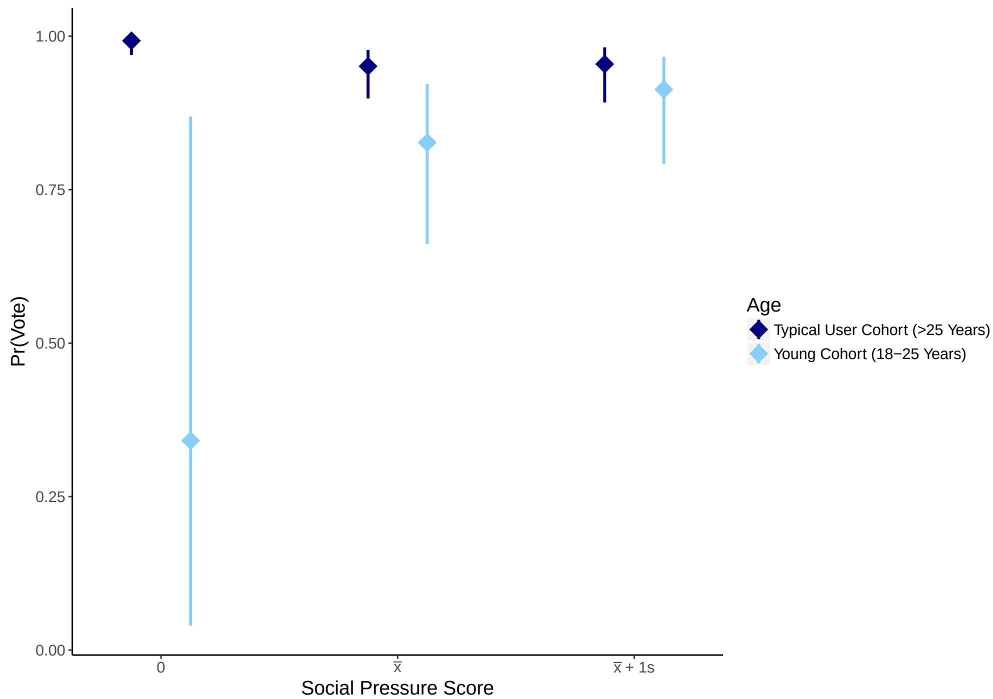
(a) Model 1



(b) Models 2 & 3

N=352. Points are logistic regression coefficients with 90% standard error bars (p¡0.1). Data Source: Facebook.com, Miami-Dade Elections Department, Oklahoma State Election Board, Wake County Board of Elections, Erie County Board of Elections

Figure 39: An Individual's Probability of Voting,
Conditional on Age



Points are predicted probabilities with simulated 90% confidence intervals, generated from logistic regression coefficient estimates (Model 1).

To interpret the substantive effects of these results, predicted probabilities are calculated. Figure 39 plots the probability of turnout for the Young User cohort and the Typical User cohort using Model 1 estimates. These scores are plotted across three values of social pressure: zero, the mean of $Social\ Pressure$ ($\bar{x}$), and one standard deviation above the mean, $\bar{x}+1s$.[56] One standard deviation below the mean produces a negative value for $Social\ Pressure$, which is not realistic. Setting the value to zero represents little or no social influence from Facebook's network, which is achievable in the data.[57] At all levels of social pressure, $Pr(Vote)$ for the Young User cohort is lower than that of the Typical User cohort. At the highest level of $Social\ Pressure$ ($\bar{x}+1s$), the likelihood of turnout among the Young User cohort was 91% compared to 95% among the Typical User cohort.

[56] The values used to determine the predicted probabilities are the mean and one standard deviation above the mean for the two remaining terms used in the three-way interaction, $Friends$ and $Years$.
[57] This value of zero is conceptually different than a value of zero representing an individual in our sample without a Facebook account. As individuals self-select onto this platform, there will be differences in the predicted probabilities of a user with a small network, even at zero, compared to an individual without a Facebook account.

This finding provides support for Young User Effect Hypothesis. As social pressure increases along the x-axis, we observe that $Pr(Vote)$ increases for the Young User cohort, though it never exceeds $Pr(Vote)$ values for the Typical User cohort.

The increase in $Pr(Vote)$ among Young Users occurs despite the negative interaction coefficient ($log(Friends) * Years * Age$ =18:25, Figure 38). Due to the three-way interaction, the marginal effect of Age on Pr(Vote) will vary linearly with $Friends$ and $Years$ (Berry, DeMeritt, and Esarey 2010).[58] The marginal effect of Age on the probability of voting is:

$$\frac{\partial E(Y)}{\partial Age} = (\beta_{Age} + \beta_{AgeYears}Yr) + (\beta_{AgeFriends} + \beta_{AgeFriendsYears}Years)Friends \tag{8}$$

In Figure 38, we can observe that the coefficients for $Friends * Age$ =18:25 and $Years * Age$ =18:25 are positive.[59] Once the interaction between age and social media use is accounted for, the effect of Facebook *within* the age cohorts can be observed. The three-way interaction controls for the fact that the Young User cohort uses Facebook at higher rates. Once social media use is held constant, the effect of age on $Pr(Vote)$ is available. This interaction determines how social media use influences the two age cohorts beyond the fact that younger individuals are more likely to use social media platforms.

These findings support the Positive Social Pressure Hypothesis: Facebook users in the Young User cohort experience an increase in $Pr(Vote)$ as Social Pressure increases. Social pressure has a positive effect on the Young User cohort. This relationship is demonstrated by the positive and significant $Friends * Years$ coefficient in Figure 38. The Negative Social Pressure Hypothesis anticipated a negative relationship between an increase in $Social\ Pressure$ and $Pr(Vote)$. Increased

[58] The marginal effect of Age on $Pr(Vote)$ depends on the values at which all other independent variables are set, as this effects $Pr(Vote)$ (and therefore, the effect of Age).

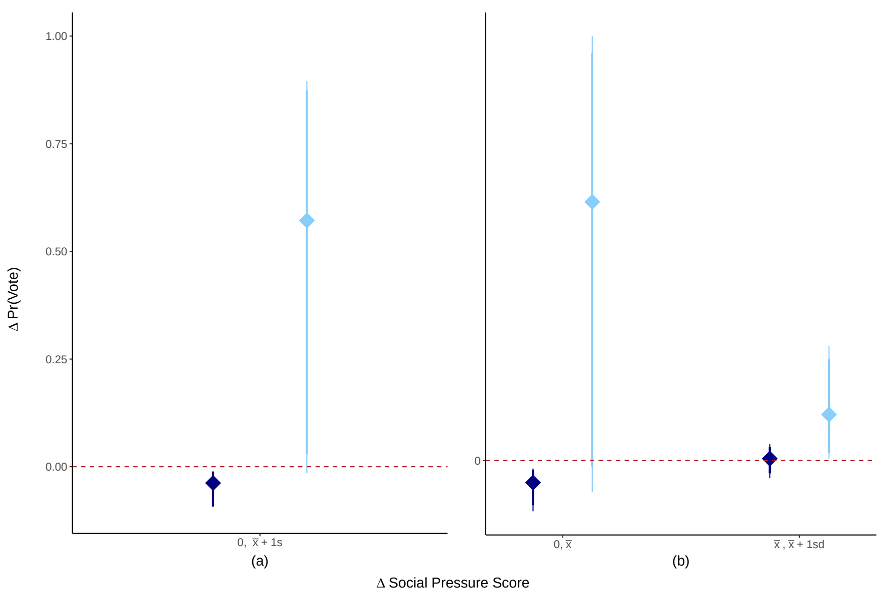
[59] The change in $Pr(Vote)$ when Age=18:25 (the Young User cohort) is dependent not only on the coefficient of Age=18:25 and $log(Friends) * Years * Age$ =18:25, but also the coefficient for the two-way interactions between $Friends * Age$ =18:25 and $Years * Age$ =18:25 and the values of these variables.

exposure to social norms that place little value on voting was predicted to produce a negative relationship. However, we observe a significant increase in $Pr(Vote)$ when the user shifts from $Social\ Pressure = 0$ to $Social\ Pressure = \bar{x}$. No evidence is found that the group norms of the Young User cohort have a negative impact on voting. Interestingly, the effect of social pressure is negative for the Typical User cohort. We can also observe a decrease in $Pr(Vote)$ among the Typical User cohort across all levels of $Social\ Pressure$ (Figure 39).

First differences are calculated to determine if the changes in $Pr(Vote)$ between the points at all three levels of $Social\ Pressure$ are significant. The findings in Figures 40(a) and (b) provide evidence for the Magnitude of Effect Hypothesis: Exposure to social pressure will cause a greater change in $Pr(Vote)$ for Facebook users in the Young User cohort than the Typical User cohort. Figure 40(a) shows the change in $Pr(Vote)$ when $Social\ Pressure$ increases from 0 to $\bar{x}+1s$. Within the Young User cohort, the probability of voting increases by 57% and is statistically significant. In the Typical User cohort, the probability of voting decreases by just 3% when $Social\ Pressure$ increases from 0 to $\bar{x} + 1s$. Figure 40(b) shows the change in $Pr(Vote)$ when $Social\ Pressure$ increases from 0 to $\bar{x}$ and $\bar{x}$ to $\bar{x}+1s$. The probability of voting increases by 8% for the Young User cohort as $Social\ Pressure$ increases from $\bar{x}$ to $\bar{x}+1s$; this change is statistically significant. Though the change in $Pr(Vote)$ as $Social\ Pressure$ increases from 0 to $\bar{x}$ is large, it is not statistically significant. The large confidence intervals associated with the predicted values of $Social\ Pressure$=0 in Figure 40(b) is likely an artifact of the data. Very few users in the Young User cohort have low social pressure networks, as displayed in Figure 34. This pattern occurs in both Figures 40(a) and (b). In the Typical User cohort, the change in the probability of voting is less than 1% and is not statistically significant. Second differences are estimated in Figure 41. These estimates provide evidence that the changes observed between the Young User and Typical User cohorts in Figures 39 and 40 are significantly different.

Similar patterns in predicted probabilities are observed when using Model 2 estimates.[60] The Typical User cohort votes at higher rates than the three remaining cohorts. This finding supports the Young User Effect Hypothesis. The interesting finding is that only the Young User cohort is significantly different from the Typical User cohort. The difference in $Pr(Vote)$ between older Millennials and Typical Users is not significantly different. Older Millennials behave more similarly to Typical Users than their Millennial counterparts within the Young User cohort.

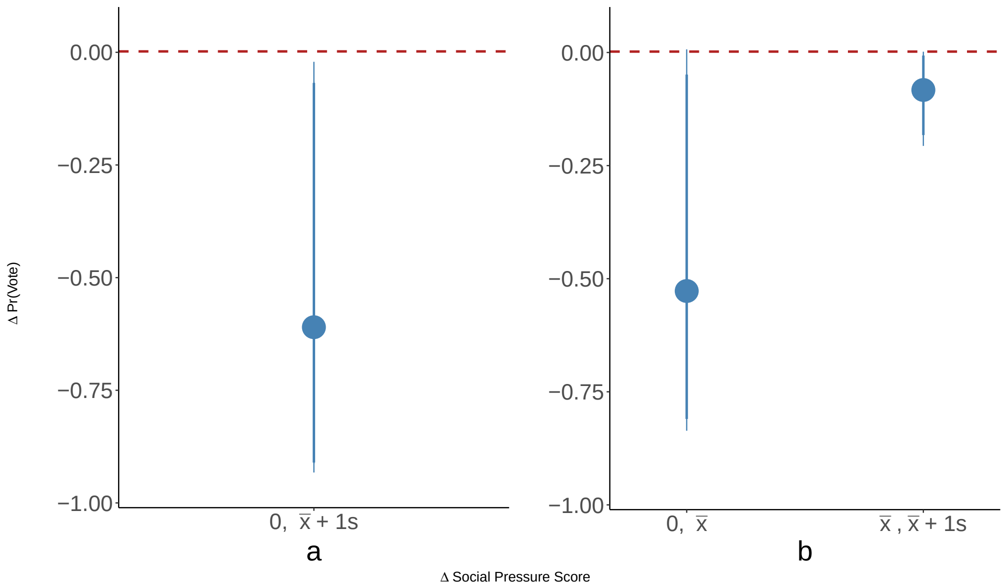
Figure 40: Change in Probability of Voting Across Social Pressure Scores, Conditional on Age



Points are first differences with simulated 95% confidence intervals (thin bar) and 90% confidence intervals (thick bar), generated from Model 1 logistic regression coefficient estimates.

[60] Using Model 2 estimates, the predicted probabilities, first differences and second differences are plotted for the ordinal age measure, see Figures 58, 59, and 60 in Appendix 9.

Figure 41: Change in Probability of Voting Across Social Pressure Scores and Age



Points are second differences with simulated 95% confidence intervals (thin bar) and 90% confidence intervals (thick bar), generated from logistic regression coefficient estimates.

Conclusion

This paper investigates the effect of online social pressure and how its impact varies based on the level of digital socialization within age cohorts. I find that Facebook use has a unique effect on turnout for each age cohort within the analysis, both the Young User cohort (18- 25 years of age) and the Typical User cohort (over 25). This effect varies in both magnitude and direction. Young users receive more influence from online social pressure; increases in the level of social pressure received have a large, positive effect on their probability of voting. Older users in the sample receive less online social pressure; increases in the level of social pressure have a small, negative effect on the probability of voting for this age cohort. The model uses an interaction term to test the significance of the relationship between social media use, age and turnout. This method controls for differences in Facebook use by members of the two cohorts. Young users are more likely to use Facebook than older users, but they are also less likely to vote than older citizens. Once differences in rates of use *between* age cohorts are accounted for, the model is able to estimate and compare how Facebook use influences $Pr(Vote)$ within each cohort.

Younger users tend to use online forms of participation and value actualizing norms of citizenship rather than dutiful norms such as voting. However, increases in online social pressure from peers also increases the likelihood of voting for young users. Even if online social networks lack social pressure to vote, they indirectly influence voter turnout by fostering social capital formation. Refining and sharing civic skills and political knowledge leads to the development of politically relevant social capital which encourages political participation. Another possibility is that voting may be more important to young citizens than expected. Future research can better estimate whether social media use has a direct or indirect impact on turnout among young voters by exploring the content of messages within this group.

The uses and gratifications approach may explain the adverse effect of Facebook use on members of the Typical User cohort. This finding runs contrary to the social norms of this group, which usually promote voting. For the older individuals in the sample, face-to-face political discussion networks have already been established, as well as norms of offline political participation. This cohort may not be seeking political outcomes in their social media use and discussion on this platform may be limited to non-political topics. This stands in contrast to young individuals, who use social media for both political and non-political reasons. Typical users who happen to use the platform extensively will not be exposed to political norms or develop politically relevant social capital, which may inadvertently result in a lower likelihood to engage in politics.

The effects of social media use and digital socialization have implications for the future of democratic citizenship. Understanding the impact of digital socialization on young citizens is crucial due to the unique relationship this group has with technology. For young individuals, social media is a part of day-to-day life; online influence may become indistinguishable from offline influence. Younger generations have experienced unprecedentedly high levels of digital socialization. Prior generations experienced socialization within face-to-face groups, including parents, members of the primary network, and the education system (Campbell et al. 1960). Social media use expands the boundaries of influence beyond one's immediate primary network and socioeconomic status. These changes may influence political ideology as well as participation patterns. Social media use introduces skills that can be used to acquire political information and participate politically, lowering the barriers to participation. These opportunities may alter the effect that age and socioeconomic status traditionally hold on civic skill development and political engagement.

Online interactions increase transparency: a user's activity is more visible to others online compared to an offline setting. This factor may increase the impact that online social networks have on members as users can monitor and enforce compliance with greater ease. A concern with social pressure is that it can be replicated through only a few sources without truly being a social norm (Lupia and Sin 2003; Margetts et al. 2015). Social media platforms may be used to present minority opinions as social norms through "likes" and "shares". Another issue is political misinformation available online and its influence on political outcomes. People depend on interpersonal discussion networks to obtain political information, yet information via social media networks does not receive the same vetting process as news obtained through formal sources. A recent example of this phenomenon is the distribution of political misinformation using social media platforms during the 2016 US Presidential election. Due to the ease with which information may be distributed online, political misinformation poses consequences for political decision making.

Further research into the relationship between digital socialization, online social norm transmission, and political outcomes is necessary as society becomes increasingly dependent on online interactions. A weakness of this study is that the data is limited to registered voters only. These individuals are more likely to vote and are generally more politically active as a result of the norms within their network. The magnitude and direction of the effect may be different for users who belong to networks that do not value political participation. However, researchers should still be able to observe *differences* in effect between age groups if digital socialization has an impact on behavior. Determining the impact of social media use on political behavior in networks that do not value participation offers a broader understanding of the impact of digital socialization.

Future research would also benefit from using a more refined measure of digital socialization than age alone. Though the generational experiences of young Millennials are likely to be similar, this group came of age during a time where digital inequality was present. Internet access was tied to socioeconomic status, and Millennials without digital access during their formative years are likely to behave more like individuals in the "Typical User" cohort. User information can be gathered via survey to determine the level of access and perceived socialization to technology possessed by these individuals. The Millennial Generation allows researchers to test for many causal mechanisms due to the variation in exposure to technology *within* this generation.

5 CONCLUSION

These studies provide evidence that social media use has a positive impact on political participation, especially among young citizens. Social media networks supply social pressure to follow social norms, which serve as a selective incentive to engage in collective action. Social pressure produces engagement that is not tied to the benefit of the collective endeavor; individuals will comply with group norms to receive social rewards and avoid social sanctions. These effects are stronger for young people due to the high levels of digital socialization this group has received. Young users are more responsive to social influence online than older groups who were not socialized to social media during their formative years.

The first paper compares the effects of information transmission and social pressure in online networks using the Twitter and Facebook platforms, respectively. A greater increase in participation among Facebook users provides evidence that social factors offer a greater impetus for change than the information/cost-reducing aspects of social media use found on Twitter. In strong-tie networks, social pressure transmitted between members offers the social/psychological selective incentives needed to engage in collective action. The second paper looks further into social pressure available on Facebook, developing a measure of social pressure from publicly available Facebook data. This social pressure variable differentiates between individuals who receive high exposure and low exposure to social pressure to follow group norms. The level of social pressure is determined by observable characteristics of their online network, namely Friend count and their years of membership on the platform. This provides evidence that social factors impact political participation. The final paper investigates if the effects of social pressure vary due to the level of digital socialization an individual received during their formative years. Age cohorts are used to represent a user's level of digital socialization. Online social pressure has a greater effect on young users compared to older users.

The difference between these age cohorts is in their level of digital socialization: young individuals were socialized to social media use during their childhoods, while older users were not.

Future Work

Online participation

These papers look only at offline forms of political participation as the dependent variable. Future research would benefit from examining online forms of political participation using the framework presented. Online forms of participation include (but are not limited to) political posts, sharing political information, and online campaign contributions (Margetts et al. 2015). Online participation has increased in recent years, especially among young citizens (Mossberger, Tolbert, and Stansbury 2003). Political parties have responded to these changes by directing more effort at online mobilization and have even changed their organizational structures to accommodate a loose, less hierarchical form that is more popular among potential voters (Ward and Gibson 2008; Davis et al. 2009; Margetts 2001). Exploring the causal mechanisms driving online participation improves understanding of online social interaction and how it compares to and supplements traditional forms participation and social interaction.

Formal vs. Informal Sources

These papers examine the network structure of platforms, looking at each platform as a representation of a "pure" strong-tie or weak-tie network. While this approach sheds light on general trends that exist within each network structure, it minimizes the true complexity of online social networks. Future research should explore the variation in the strength of ties within platforms. Social media platforms are a collection of social ties, both strong and weak, formal and informal. Though certain network structures are more efficient at transmitting either social norms or information, they are likely able to support the opposing feature to some extent. Exploring the influence of both strong and weak ties *within* a social media platform furthers the investigation completed in the first chapter of this dissertation. Formal sources represent a weak tie network connection, as the relationship is not socially close. Researchers could also compare the impact of informal sources that share a strong social tie with a user to informal sources that share a weak tie. I propose using a content-based approach focusing on a platform that easily supplies text data, such as Twitter. Though Twitter is primarily a heterogeneous network of weak social ties, strong social ties and messages of social pressure may be present on the platform. Having access to the content of messages will provide more guidance on whether information-based or social pressure-based messages were more effective in changing behavior. Researchers can also determine what topics and actions were more likely to create behavior change.

Online networks are combinations of interpersonal discussion networks and formal media sources available on an interactive platform. Social media is highly interactive, allowing users to become engaged with formal news sources *and* with other individuals. The strong-tie/weak-tie hypotheses can be applied to this setting to investigate the impact of formal news sources compared to informal social networks. This research question extends from the early Columbia studies, which found that informal social networks outweighed the effects of formal media sources in influencing voter choice (Lazarsfeld, Berelson, and Gaudet 1948). Has the new formal media environment altered this finding? Formal media sources have evolved from one-way streams of information to interactive media environments. The ability of individuals to engage with formal media sources by commenting on public news forums and social media platforms changes the nature of formal news dissemination. Formal news has the potential to reach more people through new communication technologies and may stimulate engagement as a result of the increased interactivity these sources can provide. In addition to interacting with the news media, these platforms can also increase discussion between users. Individuals rely on their social networks to act as a filter and provide easily digestible information, lowering the cost of acquiring knowledge (Mutz and Young 2011). Interpersonal communication mitigates the impact of formal media sources, including how campaign information influences political participation and knowledge (Cho et al. 2009). The relationship between formal and informal news sources becomes increasingly intertwined on social media platforms. Bridging between formal and informal news sources are opinion leaders, members of a community who take on the role of obtaining political information and spreading this information to others (Katz and Lazarsfeld 1955). This was primarily a phenomenon among political elites and organizations, who had electoral incentives to overcome the cost of gathering and disseminating information (Zaller 1992; Margetts et al. 2015). Social media sites allow individuals to take on the role of opinion leaders due to the ease of acquiring and spreading information with the goal of influencing others (Mutz and Young 2011).

Additionally, political information may be able to reach individuals who would not have received exposure in traditional settings due to disinterest. Political information acquisition becomes a 'by-product' of pursuing entertainment (Baum 2003). Information distribution using digital communication technology is cheap, giving news sources more opportunities to distribute content that may deviate from their usual entertainment-oriented goal at little to no cost. Sources that are known for popular news coverage may provide information on hot-button political issues. Social media platforms can serve as a 'gateway' to political discussion.

To access the relationship between formal and informal sources of information, researchers need to compare the influence of each source while holding the platform constant. I propose using Twitter data. This data source eliminates many of the issues with collecting interpersonal communication data as public Twitter data is easily accessible. Innovations in technology have increased the ability to observe individual behavior including social interaction and how individuals acquire and use political information. These innovations have produced new questions, but also offer opportunities to explore how changes in technology influence political behavior.

APPENDICES

1 Appendix

Survey questions used to construct independent variable

Twitter

Question: Did you use Twitter to send or receive information about the Jan 25 protests during the protests?
Response Options:

1. No
2. Occasionally
3. Regularly

Facebook

Question: Did you use Facebook to send or receive information about the Jan 25 protests during the protests?
Response Options:

1. No
2. Occasionally
3. Regularly

Survey questions used to construct dependant variable

Each response option was a dichotomous "yes" or "no".

SMS

Question: Did you forward text messages or share via SMS, through conversation, text messaging, or the Internet (select all apply)?
Response Options:

1. No
2. Forwarded SMS
3. Conversation
4. Another SMS
5. The Internet

Phone

Question: Did you share what you learned from phone calls through calling others, other conversation, text messaging, or the internet (select all apply)?

1. No

2. Called others
3. Live conversation
4. Text message
5. The Internet

Satellite TV

Question: Did you share what you learned on Satellite through conversation, text messaging, or the Internet (select all apply)?

1. No
2. Phone
3. Live conversation
4. Text message
5. The Internet

Radio

Question: Did you share what you learned on the radio through conversation, text messaging, or the Internet (select all apply)?

1. No
2. Phone
3. Live Conversation
4. Text message
5. The Internet

Newspapers or Political Writing

Question: Did you share what you learned from Newspapers or Political writing through conversation, text messaging, or the Internet (select all apply)?

1. No
2. Phone
3. Live Conversation
4. Text message
5. The Internet

Twitter

Question: Did you share what you learned on Twitter through conversation, text messaging, or the Internet (select all apply)?

1. No
2. Retweeting
3. Conversation
4. Text messages
5. The Internet
6. Other

Facebook

Question: Did you share what you learned on Facebook on with others on Facebook, or through conversation, text messaging, or the internet (select all apply)?

1. No
2. Facebook
3. Live Conversation
4. Text message
5. The Internet

Blogs

Question: Did you share what you learned on blogs on your own blogs through conversation, text messaging, or the internet (select all apply)?

1. No
2. Blogging
3. Live Conversation
4. Text message
5. The Internet

Email

Question: Did you share what you learned on E-mail through E-mail or through conversation, text messaging, or the Internet (select all apply)?

1. No
2. Emailing
3. Live Conversation
4. Text message
5. The Internet

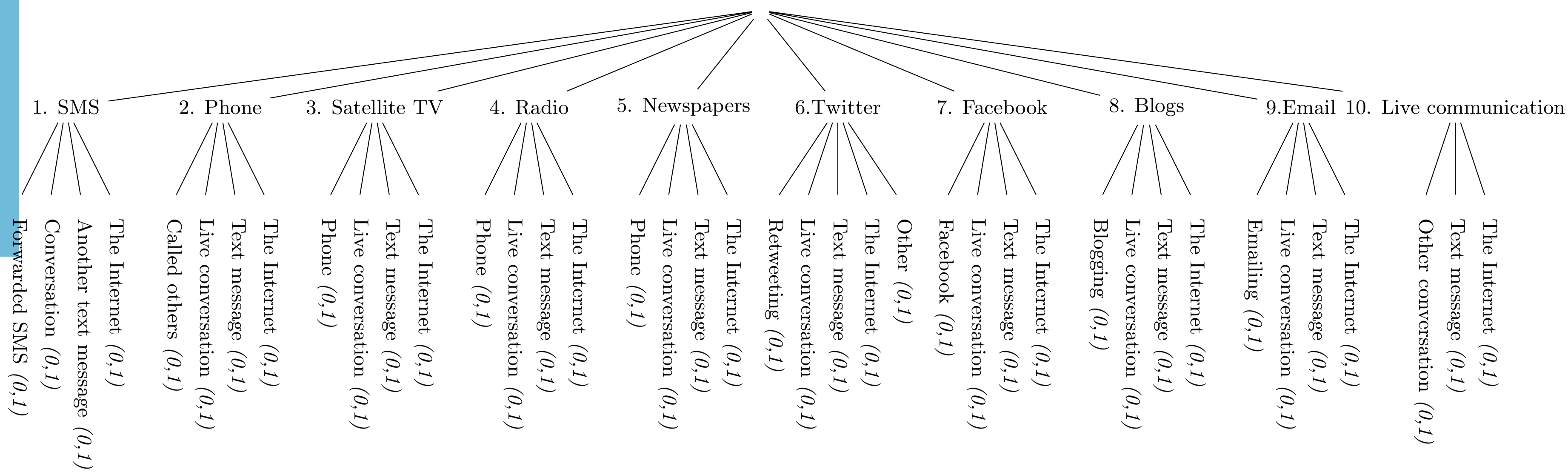
Live Communication

Question: Did you share what you learned through live communication in other conversations, text messaging, or the Internet (select all apply)?

1. No
2. Other Conversation
3. Text message
4. The Internet

Figure 42: Constructing the dependant variable

Survey Questions: Did you share what you learned through source 1-10(select all that apply)



Note: The respondent answered whether they shared the information received through sources 1-10 via three to five outlets (The Internet, Text message, Live conversation, etc.). This was a dichotomous measure, an answer of “no” was coded “0”, “yes” was coded “1”. The sum of these values(in italics) was taken to create the dependent variable, the number of acts of participation committed by an individual respondent.

2 Appendix

Table 6: The Effect of Social Media Network Structure on Individual Acts of Participation (Total DV)

	Dependent variable:	
	Total Acts of Participation	
	(Model 1)	(Model 2)
Facebook Use	1.501***	1.439***
	(0.138)	(0.143)
Twitter Use	1.367***	0.352
	(0.209)	(0.627)
Prior Protest Participation	0.508**	0.496**
	(0.229)	(0.229)
Prior Organization Membership	0.598**	0.576**
	(0.238)	(0.238)
Phone Conversation	2.335***	2.343***
	(0.397)	(0.396)
Live Conversation	2.017***	1.971***
	(0.425)	(0.426)
SMS Use	0.647***	0.677***
	(0.235)	(0.236)
Blog Use	1.356***	1.401***
	(0.374)	(0.374)
Age	0.044***	0.043***
	(0.013)	(0.013)
Female	0.093	0.091
	(0.251)	(0.251)
Education	0.202***	0.205***
	(0.076)	(0.076)
Facebook Use*Twitter Use		0.592*
		(0.345)
Constant	−3.055***	−2.938***
	(0.919)	(0.920)
Observations	1,034	1,034
R^2	0.324	0.326
Adjusted R^2	0.303	0.305

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

Data Source: Tahrir Data Project. Entries are OLS regression coefficient estimates,with standard errors in parenthesis. Location fixed effects are also estimated but have been omitted from the table.

Table 7: Robust Regression Estimates: The Effect of Social Media Network Structure on Individual Acts of Participation

	Dependent variable:	
	Total Acts of Participation	
	OLS	Robust
	(Model 2)	(Model 2)
Facebook Use	1.439***	1.439***
	(0.143)	(0.135)
Twitter Use	0.352	0.352
	(0.627)	(0.514)
Prior Protest Participation	0.496**	0.496**
	(0.229)	(0.230)
Prior Organization Membership	0.576**	0.576**
	(0.238)	(0.242)
Phone Conversation	2.343***	2.343***
	(0.396)	(0.224)
Live Conversation	1.971***	1.971***
	(0.426)	(0.357)
SMS Use	0.677***	0.677***
	(0.236)	(0.219)
Blog Use	1.401***	1.401***
	(0.374)	(0.453)
Age	0.043***	0.043***
	(0.013)	(0.013)
Female	0.091	0.091
	(0.251)	(0.250)
Education	0.205***	0.205***
	(0.076)	(0.064)
Facebook Use*Twitter Use	0.592*	0.592*
	(0.345)	(0.308)
Constant	−2.938***	−2.938***
	(0.920)	(0.884)
Observations	1,034	1,034
R^2	0.326	0.326
Adjusted R^2	0.305	0.305
Note:	*p<0.1; **p<0.05; ***p<0.01	

Data Source: Tahrir Data Project. Entries are OLS regression coefficient estimates (Model 1) and Heteroskedastic Corrected Standard Errors (Model 2). Standard errors in parenthesis. Location fixed effects are also estimated but have been omitted from the table.

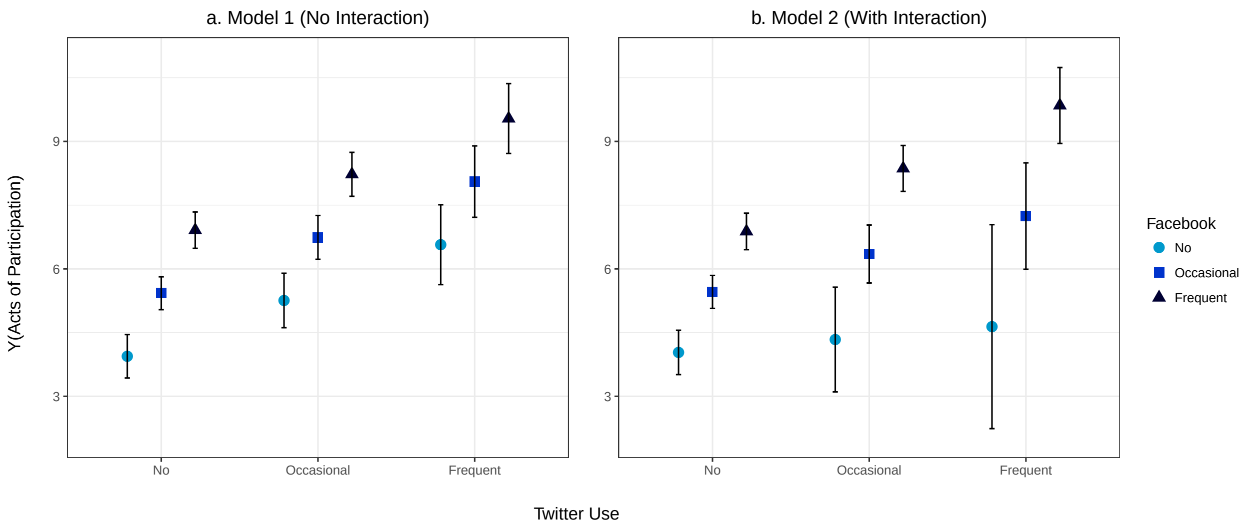
Table 8: Model Comparison: The Effect of Social Media Network Structure on Individual Acts of Participation

	Dependent variable:			
	Total Acts of Participation	Online Only	Offline Only	Face to Face
Facebook Use	1.439***	0.762***	0.391***	0.123***
	(0.143)	(0.044)	(0.089)	(0.022)
Twitter Use	0.352	0.661***	−0.339	−0.030
	(0.627)	(0.195)	(0.390)	(0.111)
Prior Protest Participation	0.496**	0.221***	0.149	0.013
	(0.229)	(0.071)	(0.142)	(0.036)
Prior Organization Membership	0.576**	0.113	0.310**	0.026
	(0.238)	(0.074)	(0.148)	(0.037)
Phone Conversation	2.343***	0.299**	1.451***	0.039
	(0.396)	(0.123)	(0.246)	(0.068)
Live Conversation	1.971***	0.108	1.507***	1.142***
	(0.426)	(0.132)	(0.265)	(0.143)
SMS Use	0.677***	−0.028	0.739***	−0.029
	(0.236)	(0.073)	(0.146)	(0.038)
Blog Use	1.401***	0.588***	0.734***	0.001
	(0.374)	(0.116)	(0.232)	(0.055)
Age	0.043***	0.007*	0.024***	−0.0002
	(0.013)	(0.004)	(0.008)	(0.002)
Female	0.091	0.028	0.138	0.004
	(0.251)	(0.078)	(0.156)	(0.040)
Education	0.205***	0.011	0.117**	0.010
	(0.076)	(0.024)	(0.047)	(0.012)
Facebook Use*Twitter Use	0.592*	0.254**	0.253	−0.026
	(0.345)	(0.107)	(0.214)	(0.060)
Constant	−2.938***	−0.376	−1.941***	−0.225
	(0.920)	(0.286)	(0.572)	(0.188)
Observations	1,034	1,034	1,034	816
R^2	0.326	0.516	0.212	0.156
Adjusted R^2	0.305	0.501	0.188	0.123

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

Data Source: Tahrir Data Project. Entries are OLS regression coefficient estimates,with standard errors in parenthesis. Location fixed effects are also estimated but have been omitted from the table.

Figure 43: Predicted Values: Acts of Participation Given the Level of Twitter Use



Note: predicted values are derived from OLS regression estimates with standard error bars. A full table of regression estimates is available in Table 6, see Appendix 2.

3 Appendix

Table 9

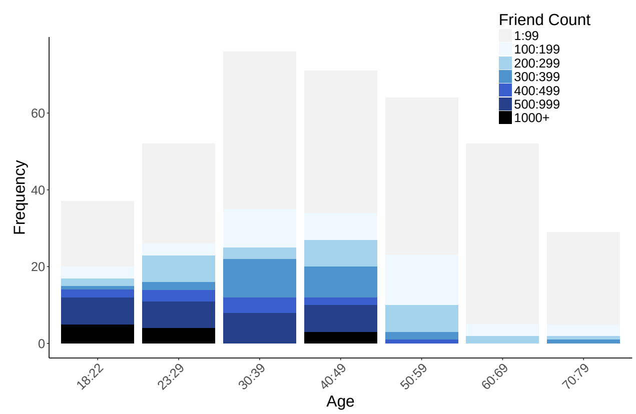
Statistic	N	Mean	St. Dev.	Min	Max
GENERAL2012 (Y)	929	0.736	0.441	0	1
Facebook2012	984	0.387	0.487	0	1
Years	381	2.843	1.478	1	7
Friends2012	381	171.142	282.201	1	1,749
log(Friends)	381	1.118	2.191	0	7.467
log(Friends)*Years	381	8.671	10.960	0	50.366
Age2012	984	48.920	18.232	18	99
Female	958	0.555	0.497	0	1

Table 10: Percentages of Facebook Use and Voter Turnout by Age group

Age Group	% of All Registered Voters with FB	% of Voters with FB	% of Abstainers with FB	Vote- Abstain
18 : 22	45.9	46.9	48.1	-1.3
23 : 29	34.5	41.1	28.8	12.2
30 : 39	32.7	37.3	23.7	13.6
40 : 49	31.5	38.3	19.5	18.7
50 : 59	24.3	24.1	28.6	-4.5
60 : 69	20.4	22.0	17.6	4.3
70 : 99	10.3	12.1	5.0	7.1

Note: FB refers to a Facebook account

Figure 44: Friend Count Per User (By Age)



Note: Data is from the 2012 election.

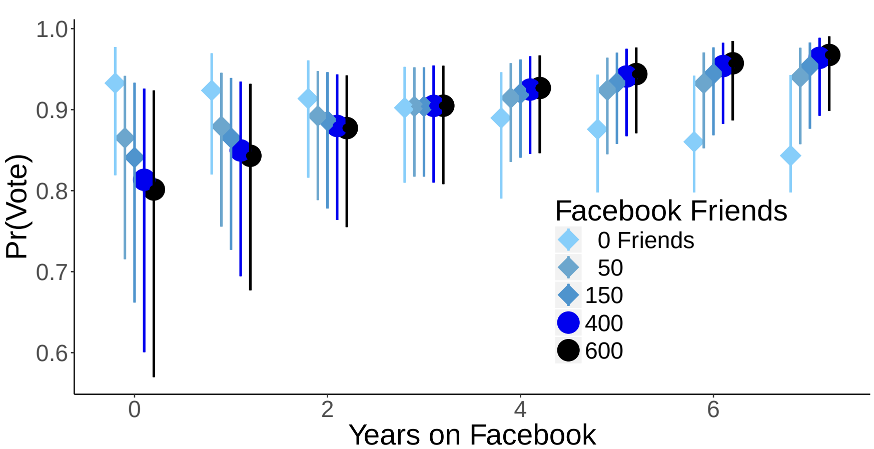
4 Appendix

Table 11: The Effect of Facebook Use on Individual Voter Turnout During the 2012 General Election

	Dependent variable:		
	General Election (2012)		G2012FULL
	Model.1	Model.2	Model.3
Facebook Use	0.383** (0.172)		
log(Number of Friends)		0.015 (0.051)	−0.193* (0.115)
Years on Facebook		0.079 (0.097)	−0.135 (0.143)
Age	0.026*** (0.005)	0.040*** (0.010)	0.038*** (0.010)
Female	0.071 (0.162)	0.347 (0.279)	0.363 (0.280)
Party ID	1.114*** (0.228)	0.998** (0.414)	1.065** (0.418)
State	0.684*** (0.241)	0.755* (0.420)	0.758* (0.422)
log(Number of Friends)*Years on Facebook			0.066** (0.033)
Intercept	−1.419*** (0.325)	−2.138*** (0.674)	−1.482** (0.752)
Observations	908	352	352
Log Likelihood	-472.234	-164.031	-161.919
Akaike Inf. Crit.	964.469	350.062	347.839
Note:	*p<0.1; **p<0.05; ***p<0.01		

Entries are logistic regression coefficient estimates, with standard errors in parenthesis. Data Sources: Miami-Dade Elections Department Public Services Section, Oklahoma State Election Board, Wake County Board of Elections, Erie County Board of elections, Facebook.com.

Figure 45: A. An Individual's Probability of Voting, Conditional on Facebook Network Size



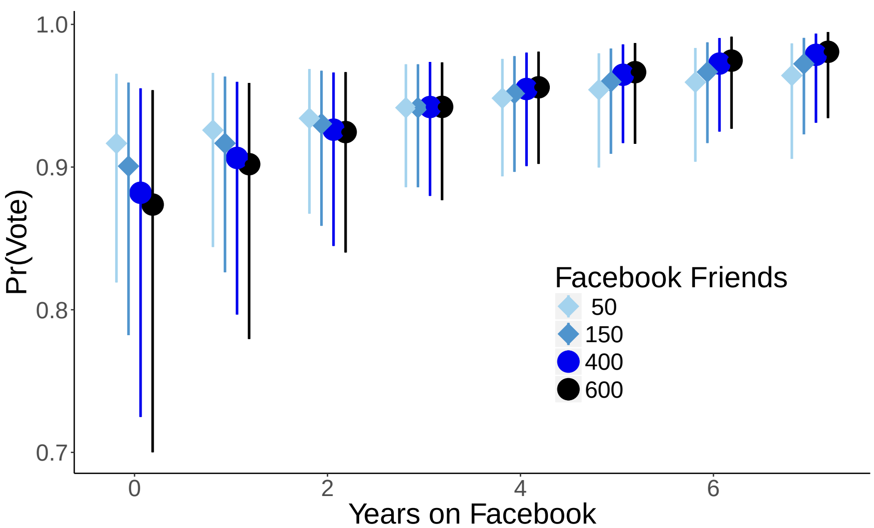
Points are predicted probabilities with simulated 95% confidence intervals, generated from logistic regression coefficient estimates.

Table 12: Full Dataset: The Effect of Facebook Use on Individual Voter Turnout During the 2012 General Election

	Dependent variable:		
	General Election (2012)		
	Model.1	Model.2	Model.3
Facebook Use	0.383**	0.243	0.799*
	(0.172)	(0.320)	(0.448)
log(Number of Friends)		0.005	−0.173
		(0.049)	(0.108)
Years on Facebook		0.045	−0.141
		(0.088)	(0.133)
Age	0.026***	0.027***	0.027***
	(0.005)	(0.005)	(0.005)
Female	0.071	0.074	0.078
	(0.162)	(0.162)	(0.162)
Party ID	1.114***	1.110***	1.124***
	(0.228)	(0.229)	(0.229)
State	0.684***	0.684***	0.677***
	(0.241)	(0.241)	(0.242)
log(Number of Friends)*Years on Facebook			0.057*
			(0.031)
Intercept	−1.419***	−1.440***	−1.439***
	(0.325)	(0.327)	(0.328)
Observations	908	908	908
Log Likelihood	-472.234	-472.093	-470.336
Akaike Inf. Crit.	964.469	968.185	966.671
Note:	*p<0.1; **p<0.05; ***p<0.01		

Entries are logistic regression coefficient estimates, with standard errors in parenthesis. Data Sources: Miami-Dade Elections Department Public Services Section, Oklahoma State Election Board, Wake County Board of Elections, Erie County Board of elections, Facebook.com.

Figure 46: An Individual's Probability of Voting, Conditional on Facebook Network Size, Age = 49 (Mean)



Points are predicted probabilities with simulated 95% confidence intervals, generated from logistic regression coefficient estimates. Small network = 50 Facebook Friends, large network = 400. , respectively.

Table 13: Determining Multicollinearity in Model 1 and 2

X	Y	Point Biserial Correlation Coefficient	P-value
$log(Facebook)$	$FacebookUse$	0.6422362	0.00
$Years$	$FacebookUse$	0.8332572	0.00

To test for possible mlticollinearity in a logistic regression model, point-biserial correlation coefficients are estimated. These coefficients are a special case of the Pearson's product-moment correlation, used when one or both variables are binary. This allows us to test if there is a statistically significant relationship between the variables.

5 Appendix

Table 14: The Effect of Facebook Use on Individual Voter Turnout During the 2014 General Election

	Dependent variable:		
	General Election (2014)		
	Model.4	Model.5	Model.6
Facebook Use	0.188		0.481
	(0.161)		(0.559)
log(Number of Friends)		−0.004	−0.132
		(0.049)	(0.128)
Years		0.045	−0.066
		(0.051)	(0.122)
Age	0.037***	0.037***	0.038***
	(0.005)	(0.005)	(0.005)
Female	−0.035	−0.032	−0.030
	(0.155)	(0.154)	(0.155)
Republican	1.339***	1.337***	1.339***
	(0.220)	(0.221)	(0.221)
State: NC	1.314***	1.299***	1.289***
	(0.230)	(0.230)	(0.231)
log(Number of Friends)*Years on Facebook	1.205**	1.205**	1.198**
	(0.490)	(0.490)	(0.491)
Intercept			0.028
			(0.025)
Constant	−3.172***	−3.204***	−3.218***
	(0.352)	(0.356)	(0.357)
Observations	812	812	812
Log Likelihood	-496.021	-495.814	-495.201
Akaike Inf. Crit.	1,012.043	1,013.628	1,016.401
Note:	*p<0.1; **p<0.05; ***p<0.01		

Entries are logistic regression coefficient estimates, with standard errors in parenthesis. Data Sources: Miami-Dade Elections Department Public Services Section, Oklahoma State Election Board, Wake County Board of Elections, Erie County Board of elections, Facebook.com.

6 Appendix

This is the 2016 version of the codebook, it is updated prior to each election to accommodate changes that Facebook made to the platform. The current edition of the codebook is compliant with the 2016 edition of the Facebook platform

Facebook Codebook

Intro

These instructions will guide you through 1)how to search/verify individuals from the Voter Registration list (Hereafter, VR list) dataset, and 2)how to extract information from the Facebook (Hereafter, FB) accounts that you find.

- This process is confidential; do not share the names of registered voters with any individual outside of those working on this particular research project. After the FB data is collected, these registered voters will be referred to in the dataset through numeric identifiers.
- These individuals are not to be contacted by the coder in any way.
- This dataset is not to be distributed.
- If you have any questions, contact me at rmbryan@buffalo.edu

Coding

- This dataset is composed of labeled **columns**(vertical), each representing a different variable, for example "FirstName". Each **row**(horizontal) represents an individual registered voter.
- The dataset is informally broken up into two types of data, Verification Data and Account Data; the coding guidelines are also divided into these two sections.
  - The header's of the Verification Data columns are highlighted in **yellow**. Input data in these columns only if it is available, if not leave blank
  - The headers of the Account Data Columns are highlighted in **blue**. Do not leave these columns blank; the cells must contain either a numerical value, URL, or 'NA' in the cell.
- There are 985 Individuals in this dataset. We will be searching for FB accounts for around 500 of them.
  - Keep in mind that only around 60% of adults use social media sites, so if you don't find that many profiles, that is not unusual
  - Also, use of social media varies by age, so you will be even less likely to find the older individuals in our dataset on Facebook.

I recommend highlighting the row you are working on so that you know you are reading from and typing content into the correct row. You can leave these rows highlighted as you go, it will not impact the dataset.

Column: Facebook2014

- Do not modify this column
- If Facebook20014 = 0(zero), the user did not have FB account that was located in 2014. For these voters, you will need to search for their accounts, see 4. Verification Data Section below.
- If Facebook20014 = 1 , the voter's FB account was already located, ignore these cases for now

Verification Data Section

This section addresses how to search for and verify the Facebook account (If Facebook2014 = 0)

1. Always start a search by typing in the First and Last name of the individual followed by their city (further instructions are provided after the table).
2. Then, look for accounts that fit the Individual Characteristics listed in the table below, which will help to verify if the FB account belongs a voter in the dataset.
   Details on how to use each characteristic are provided in the second column.

6.1 Individual Characteristics

- Columns A-Q contains information on the registered voter's characteristics; you will use this information to verify if that individual has a FB account.

- Review this table, then move on to learn how to search for the individuals using this information
- If you do not find verification data for a certain column, leave that cell blank.

6.2 Starting your search

1. Start your search by typing in the **first** and **last** name of the individual followed by their **city** into the search bar, then hit **enter**
   (a) This will bring up a page with larger pictures and more information on your search candidates (do not select from the drop down list immediately under the search bar, there is not enough information provided here).
   (b) Click on "see more" to expand your options
   - **First name, Last name and city/state are the three most important verification categories, we cannot verify the account without these three basic characteristics**
   - Only code individual accounts. Business pages or Facebook groups do not qualify.
   - Example: Type in the first name in the dataset,
   - This page of the profile is the main page, we will refer to as the user's **'Timeline'**, the PDF and URL will need to be saved from this page
2. If using "first name, last name, city" does not produce results, try the following, in this exact order:
   (a) Use the state instead of city.
   (b) Search using their middle name/ suffix.
   (c) Search using their middle name(if available), without a location.
   (d) Search first and last name only, though this may produce too many results if the name is common.
   - If a few options come up in your search, but no one stands out immediately, look briefly into the accounts that show up
   - If many options come up in your search and you cannot easily narrow them down by visual characteristics/location, move on to the next person in the spreadsheet
   - If you cannot find an account for that individual, leave that row blank, the Excel spreadsheet will code "Facebook 2016" as a zero
3. **Once you have located a Facebook account, you need to save this page as a PDF so that we have a physical record of the information**
   - On a Mac: With their FB page open, go to file, then print, then click on save as PDF, see below:

   - For a PC, you can find directions here
   - In your UBbox folder, under "FBScreenshots2016", there are four folders, one for each state.
     - Save the PDF to the correct state folder, based on what is listed in the State column in the VR list.
     - The file name should contain the **first and last name listed on the VR list**.

Column Name	**Instructions**
SampleID	Identifier
FirstName	First name of registered voter
VerFirstName	If this characteristic matched the FB account you located, **Code as 3**(place a 3 in this cell) If you receive no returns on your first try, you can use plausible nicknames, such as "Katie" instead of Katelyn. If the account you find has a plausible nickname, **Code as 3**. If you type in Katelyn Smith, and Katie Smith automatically comes up **Code as 3** If you are missing any portion of the name, click on the URL bar at the top of your browser, you will see a link like this: https://www.facebook.com/NAME
LastName	Last name of registered voter If coded 'NA'(the line will be grayed out), skip this individual, for now
VerLastName	If this characteristic matched the FB account you located, **Code as 3** If the individual is female, we have to factor in that they may have changed their name due to marriage or divorce. If you search for a certain last name, but another name appears as a result **Code as 1**. On the VR list, some women may put their maiden name in the middle name column. If this is the case, **Code as 3** Some FB users use their middle name as their last name, for example, Jennifer Ann. If this name appears, when you type in Jennifer Smith, and the middle name matches the name listed in the dataset, **Code as 3** If Jennifer Ann appears, when you type in Jennifer Smith, but there is no middle/maiden name listed in the dataset, **Code as 1**
MiddleName	Middle name/initial of registered voter
VerMiddleName	If this characteristic matched the FB account you located, **Code as 2** Some FB users provide this information, which is an additional measure of validity If many names appear when you type the name in the search bar, which may happen with common names, try inserting the middle name (Jennifer Ann Smith Miami)
Jr, Sr, II, etc.	Suffix
VerSuffix	Jr, Sr, II, etc. Similar to the middle name, this can help us narrow down our options. **Code as 1**
State	State identifier (NC, OH, FL, OK)
City2014	Within the county, which city does that individual live in
VerCity2014	If this characteristic matched the FB account you located, **Code as 2** If you search for an individual using "Firstname Lastname city (or state)" and that individual appears in the search, we will consider them as being from that city *even if* they do not list that city in their public information. If that city is listed under another section, such as their job**Code as 2** If an individual appears when you enter their name and city but you cannot find any supporting documentation on their location **Code as 1**
Age	Age of voter (in 2016)
VerAge	If this characteristic matched the FB account you located. There are two options: Some individuals may indicate the year they graduated high school, click on the "About" section, then click "Work and Education" (in the left panel) to see if a graduation date is provided. If so, subtract the year of graduation from 2016, add 18, and see if the age matches. The age found on FB can be within 1-2 of the age listed on the VR list, as their birthday is not accounted for so our count may be off, also to account for early/late graduation. If you use this method, **Code as 2.** You can also do this with college graduation year, though this is less reliable: 2016-Graduation year +22 If there is no way to determine the user's age with precision, use your judgment to determine if the person could fit in the correct age bracket. **Code as 1**
Female	Female = 1, Male = 0
Race	white, black, hispa(hispanic) and none.
VerRace	The options we will use to code are white, black and hispa(hispanic). If you are unsure, leave this column blank If 'none' is listed, just leave this cell blank. **Code as 1(less sure) or 2(more sure)** depending on your confidence.

6.3 Facebook2016

Do not alter this column; it is set up to sum the characteristic verification data columns.
If you do not find this individual, this cell will automatically be coded as a zero.

6.4 URL2016

Copy the URL from the Timeline page of the account, for example https://www.facebook.com/NAMENAME.

**You may want to complete the verification Data Section for multiple users in one chunk, before moving on to completing the Account Data Portion for these users (you can re-access the accounts you found using the URL). These tasks are different enough that transitioning from one to another may disrupt the flow of your work. This is purely a suggestion, as each person works differently

Account Data Section

This section addresses how to complete columns T-W.

6.5 Friends2016

1. On the user's Timeline, scroll down until you see "Friends" listed in the left sidebar

2. If the user's friend count is public, a number will appear to the right of the word "Friends", in the example below, we can see our user has 1,116 Friends.

3. If no friends are listed, type 'NA' into this cell (lowercase 'na' is also fine)

6.6 FacebookStartYear

Here, input the year the person started their FB account.

To do this:

1. Make sure you are on the Timeline page

2. Start scrolling down until dropdown menu appears in the upper left corner.

3. How to find the correct start date:
   - FB started in 2004/5, so any date listed before that we assume to be life events the user has inputted (which can be done 'retroactively'). These dates are unrelated to their FB start date
   - In the drop-down menu, click on the earliest date available (post 2004)
   - What we are looking for is when that individual started making real posts (not life events), comments, or added a profile picture. This will verify that they had an active account at this time

     cell.

- Note that for some people you will not see year options (only 'Timeline' and 'About').
- For these accounts, go to the Timeline and scroll down as far as you can to see the oldest piece of information, such as a profile picture or comment, and use that date.

6.7 Followers

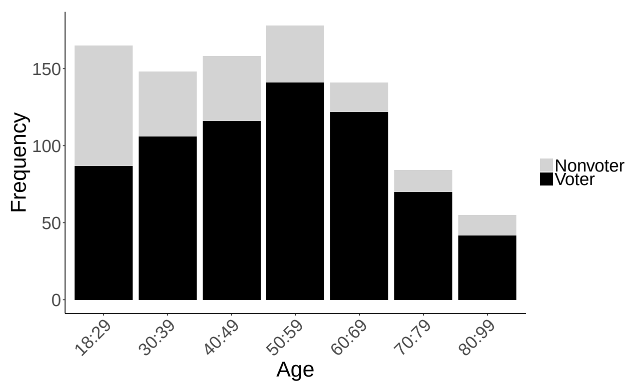
1. Click on the Friends tab, next to the 'Timeline' tab
2. If there are no followers, type in 'NA'('na')
3. If 'Followers' is listed, input this number into the dataset

Table 15

Statistic	N	Mean	St. Dev.	Min	Max
Facebook Friends	381	171.703	281.872	2	1,749
log(Friends)	381	1.118	2.191	0	7.467
Years (on Facebook)	381	2.843	1.478	1	7

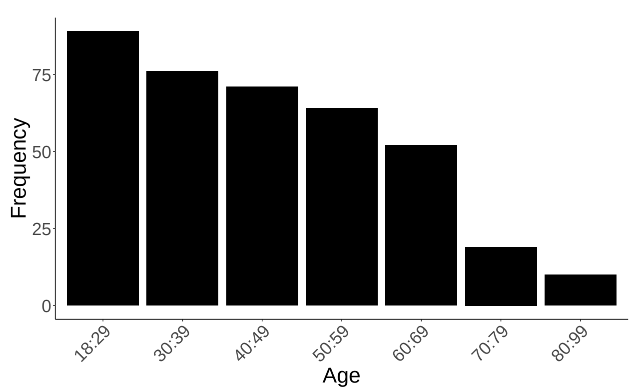
Statistic	N	Mean	Mode	Min	Max
Vote 2012	929	0.736	1	0	1
Young Cohort (18-25)	984	0.108	1	0	1
Female	958	0.555	1	0	1
Republican (=1)	984	-	1	1	4

Figure 47: Voter Turnout by Age



Notes: data is from the 2012 General Election.

Figure 48: Facebook Use by Age



Notes: data is from the 2012 General Election.

7 Appendix

Table 16: Friend Count (Per User)

Friend Count (Category)	% of Users
1 : 49 Friends	18 %
50 : 99	14
100 : 199	19
200 : 299	13
300 : 399	11
400 : 499	6
500 : 999	13
1000 : 1749	6

To investigate trends in the data, Table 16 places users into one of eight categories based on their number of Facebook Friends. Seventy-five percent of the sample had less than 400 Friends. Only 6% of users had more than 1000 Friends in their network.

Table 17: Years on Facebook (per User)

Years on Facebook	% Facebook Users
1 Year	19 %
2	20
3	30
4	18
5	6
6	4
7	2

Table 17, displays the percentage of Facebook users who have had Facebook from one to seven years; seven years is the longest amount of time a user in our sample had Facebook. In 2012, 88% of the sample had a Facebook account for four years or less.

Figure 49: Friend Count By Age

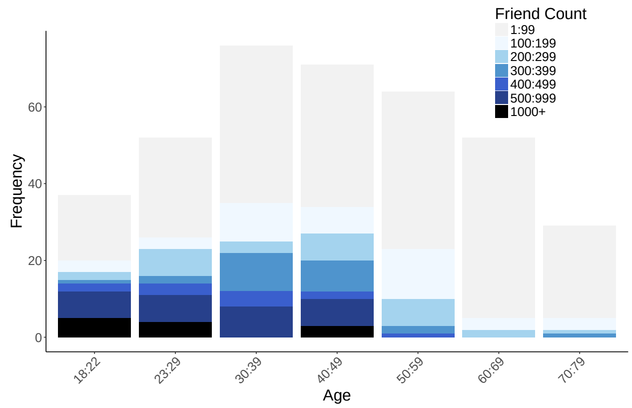


Figure 50: Friend Count and Years on Facebook Plot

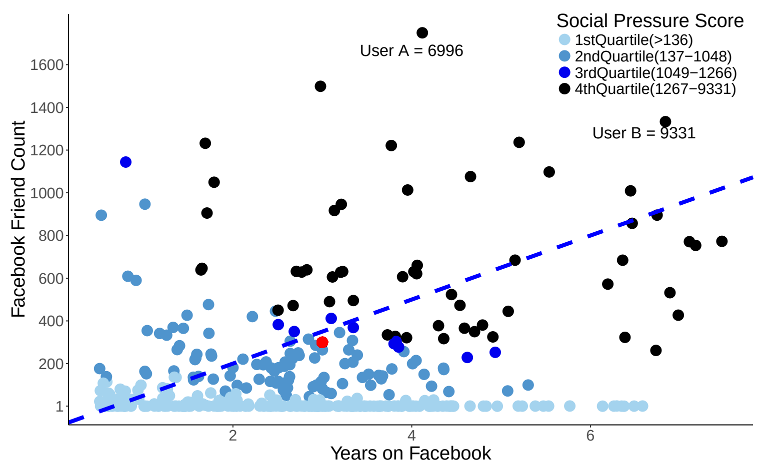
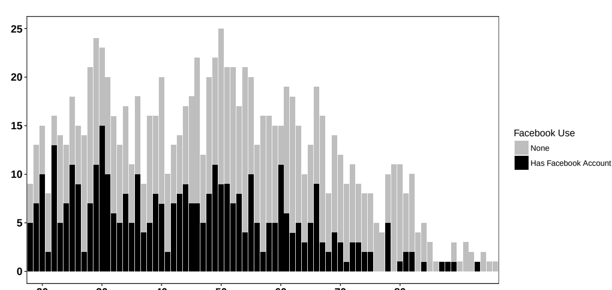
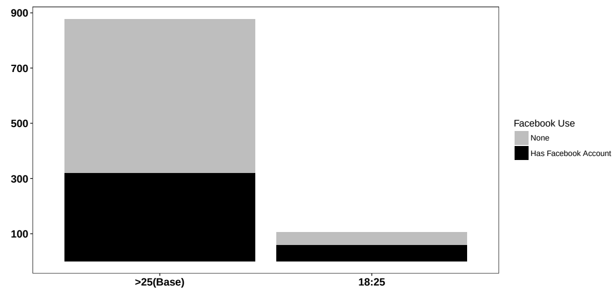


Figure 51: Facebook Use by Age



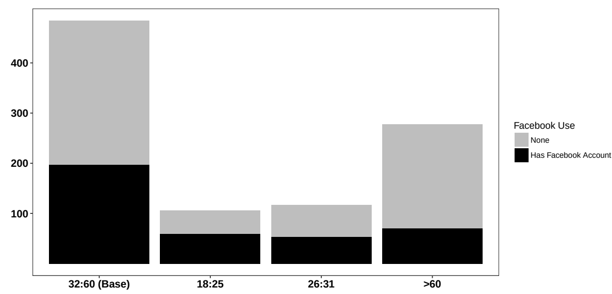
Model 4 and Model 5 use *FacebookUse* only to determine the *collective* effect that this platform has on turnout, including both social and non-social factors that may be present. Model 5 uses an interaction between *FacebookUse* and *Age* to explore how patterns of social media use may impact turnout. Models 4 and 5 are run on the full dataset,

Figure 52: Facebook Use by Age (Two Categories)



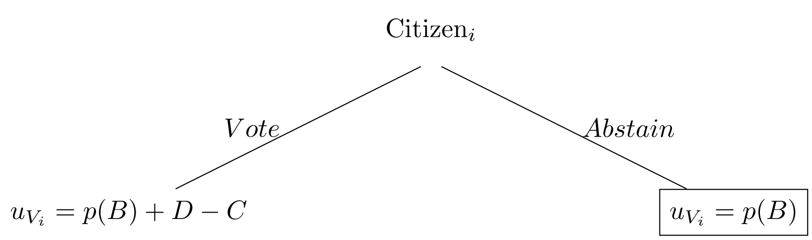
Notes: Each color category illustrates the percentage of users that fall into one of the four social pressure score categories (measured as 1st - 4th quartiles).

Figure 53: Facebook Use by age (Four Categories)



Notes: Each color category illustrates the percentage of users that fall into one of the four social pressure score categories (measured as 1st - 4th quartiles)

Figure 54: Utility of Voting Model

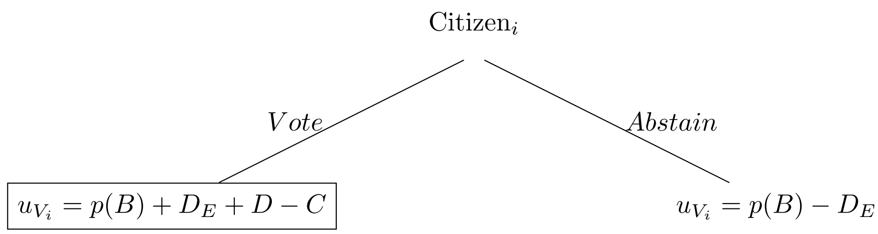


including Facebook users and nonusers. This test provides a robustness check of the effects of Facebook available.

$$Pr(Vote) = logit^{-1}(\beta_0 + \beta_{FB}FacebookUse + \beta_A Age + \beta_F Female + \beta_R Republican \\ + \beta_S State : OH + \varepsilon_i \tag{9}$$

$$Pr(Vote) = logit^{-1}(\beta_0 + \beta_{FB}FacebookUse + \beta_A Age + \beta_{FB*A}FacebookUse * Age + \\ \beta_F Female + \beta_R Republican + \beta_S State : OH + \varepsilon_i \tag{10}$$

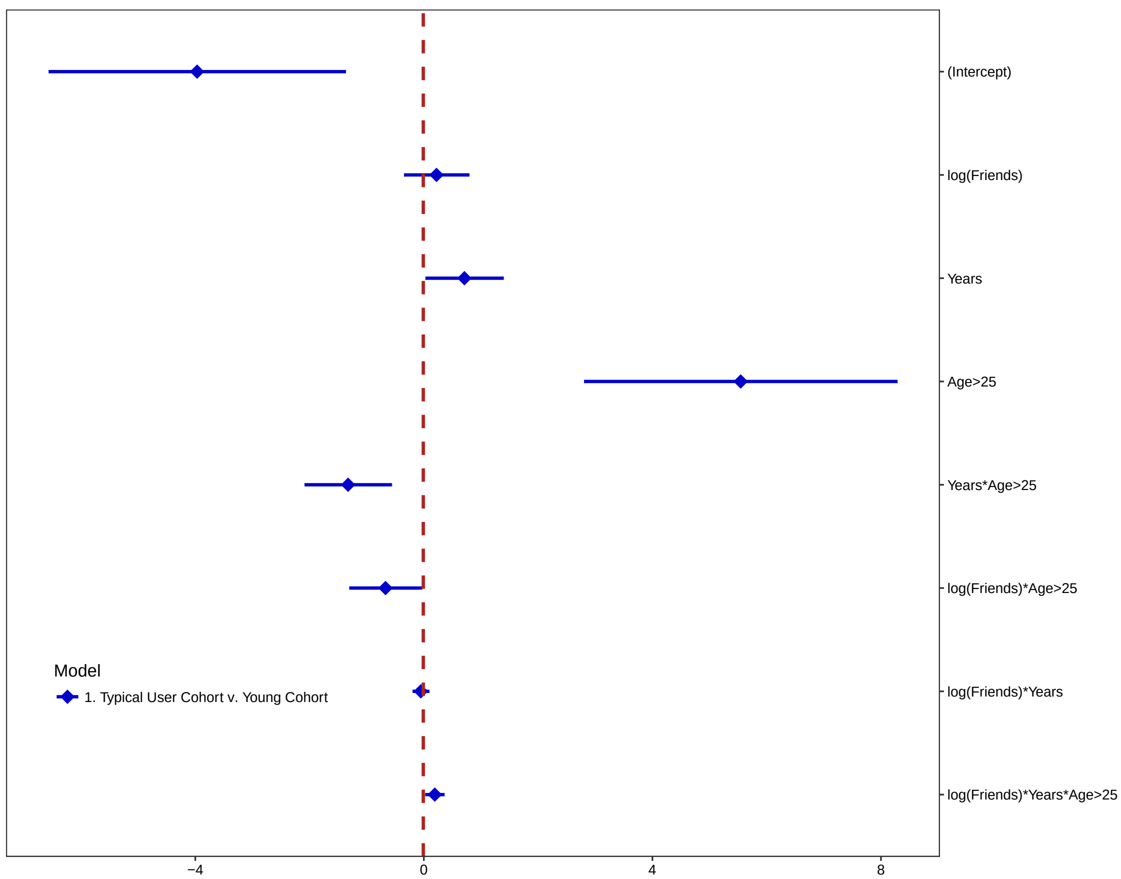
Figure 55: Utility of Voting Using Extrinsic (Social) Incentives



Note: The boxed outcomes indicate the dominant strategy in Figures 54 and 55.

8 Appendix

Figure 56: Logistic Regression Estimates (Age>25 = 1)



N=352. Points are logistic regression coefficients with standard error bars (95% =thick bar, 90% = thin bar. Data Source: Facebook.com, Miami-Dade Elections Department, Oklahoma State Election Board, Wake County Board of Elections, Erie County Board of Elections

Table 18: Results

	Model				
	(1)	(2)	(3)	(4)	(5)
log(Friends)	−0.449*** (0.160)	−0.426* (0.229)	0.507 (0.387)		
Years	−0.616*** (0.196)	−0.639** (0.307)	0.840* (0.466)		
log(Friends)*Years	0.138*** (0.048)	0.145* (0.076)	−0.146 (0.109)		
Age=18:25	−5.545*** (1.666)				
log(Friends*Age=18:25	0.671* (0.385)				
Years*Age=18:25	1.326*** (0.463)				
log(Friends)*Years*Age=18:25	−0.191* (0.101)				
Age=18:25		−5.521*** (1.790)			
Age=26:31		−1.530 (1.661)			
Age>60		0.398 (1.990)			
log(Friends)*Age=18:25		0.650 (0.419)			
log(Friends)*Age=26:31		0.128 (0.372)			
log(Friends)*Age>60		0.148 (0.594)			
Years*Age=18:25		1.353*** (0.520)			
Years*Age=26:31		0.311 (0.436)			
Years*Age>60		0.200 (0.678)			
log(Friends)*Years*Age=18:25		−0.198* (0.117)			
log(Friends)*Years*Age=26:31		−0.039 (0.103)			
log(Friends)*Years*Age>60		−0.131 (0.219)			
Age			0.130*** (0.042)		
Years*Age			−0.021** (0.010)		
log(Friends)*Age			−0.030** (0.012)		
log(Friends)*Years*Age			0.007** (0.003)		
Facebook				0.285* (0.170)	0.344* (0.186)
Age=18:25				−0.876*** (0.228)	−0.681** (0.335)
Facebook*Age=18:25					−0.363 (0.453)
Female	0.537* (0.286)	0.495* (0.293)	0.382 (0.285)	0.087 (0.160)	0.082 (0.160)
Republican	1.255*** (0.421)	1.110** (0.437)	1.089** (0.426)	1.175*** (0.225)	1.174*** (0.225)
State:OH	0.787* (0.423)	0.696 (0.436)	0.764* (0.433)	0.666*** (0.237)	0.672*** (0.237)
Intercept	1.576** (0.742)	1.668* (0.987)	−4.637*** (1.719)	−0.062 (0.237)	−0.083 (0.239)
Observations	352	352	352	908	908
Log Likelihood	−159.246	−156.759	−158.337	−480.763	−480.443
Akaike Inf. Crit.	348.492	359.519	346.674	981.526	982.885

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Entries are logistic regression coefficient estimates, with standard errors in parenthesis. Data Sources: Miami-Dade Elections Department Public Services Section, Oklahoma State Election Board, Wake County Board of Elections, Erie County Board of elections, Facebook.com.

9 Appendix

Figure 57: Interaction Effect

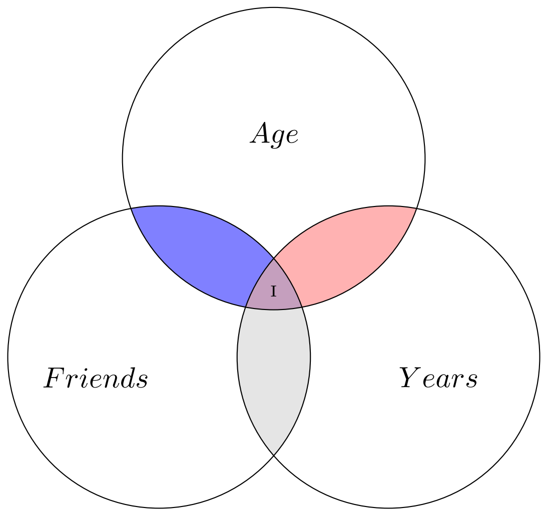
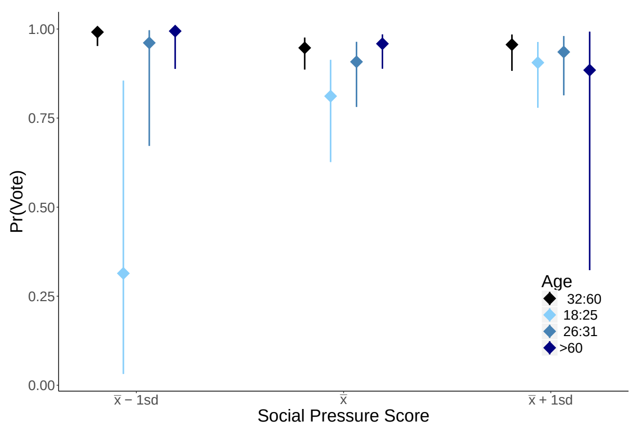


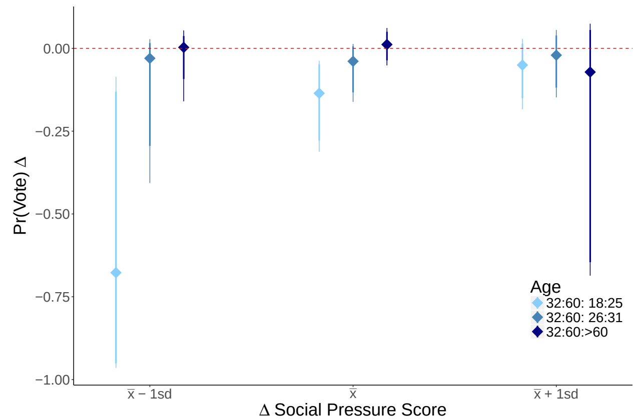
Figure 57 illustrates the three-way interaction between $Friends$, $Years$, and Age. This interaction controls for the fact that the Young Cohort uses Facebook at higher rates, illustrated by the purple shaded area labeled "Interaction". Once this relationship is removed, the secondary effect of the age and social media use on $Pr(Vote)$ is available in the coefficients for $Friends * Age$ =18:25 and $Years * Age$ =18:25, shaded blue and red, respectively (Figure 57)

Figure 58: An Individual's Probability of Voting, Conditional on Age (Model 2)



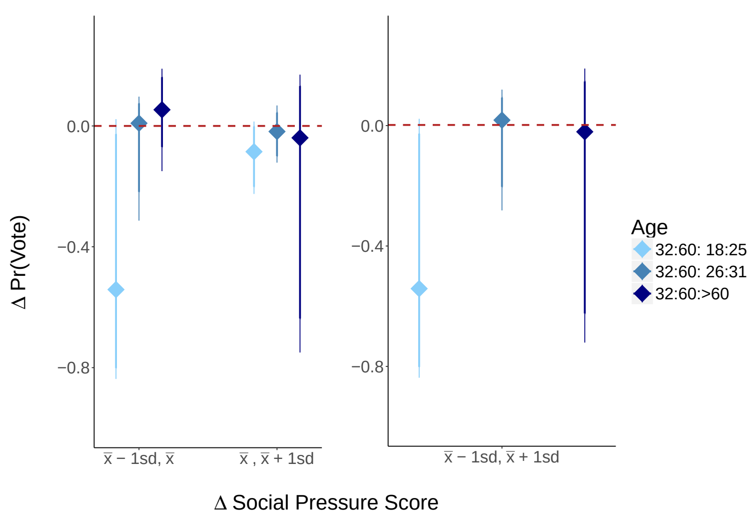
Points are predicted probabilities with simulated 90% confidence intervals, generated from logistic regression coefficient estimates (Model 2). A complete table of regression estimates can be found in Table 18, Appendix 8

Figure 59: Change in Probability of Voting Across Social Pressure Scores, Conditional on Age



Points are first differences with simulated 95% confidence intervals (thin bar) and 90% confidence intervals (thick bar), generated from logistic regression coefficient estimates.

Figure 60: Change in Probability of Voting Across Social Pressure Scores, Conditional on Age



Points are first differences with simulated 95% confidence intervals (thin bar) and 90% confidence intervals (thick bar), generated from logistic regression coefficient estimates.

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