

SOCIAL SCIENCE WITH SOCIAL MEDIA

A Dissertation

Presented to the Faculty of the Graduate School

of Cornell University

In Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

by

Scott Andrew Golder

May 2017

© 2017 Scott Andrew Golder

SOCIAL SCIENCE WITH SOCIAL MEDIA

Scott Andrew Golder, Ph. D.

Cornell University 2017

Over the past twenty-five years, electronic communication has matured from being a niche social activity mainly enjoyed by academics and engineers, to an important enabler of the daily activities of a demographically diverse population of hundreds of millions of people worldwide, augmenting, complementing, or even replacing offline methods of socializing, dating, shopping, learning, working, and engaging in political activities.

While this transition is in itself interesting, it also has significant implications for the social and behavioral sciences. The daily lives of people worldwide are now captured in detailed, event-level recordings that are time-stamped and geo-stamped, providing researchers with a new kind of observational data, enabling them to address fundamental questions about social identity, status, conflict, cooperation, collective action, and diffusion. This dissertation explores these implications, with a critical review and two empirical explorations.

Chapter one reviews existing literature and examines the methodological challenges that arise along with the opportunity provided by online behavioral data, including generalizing to the offline world, protecting privacy, and solving the logistical challenges posed by data at a larger scale than social and behavioral

scientists typically use.

Chapter two is an investigation into measuring the rhythms people experience in their mood over the course of the day, week and year. By analyzing the text of hundreds of millions of timestamped messages from the social media service Twitter, I show that there is a consistent shape to people's moods over time, including boosts in positivity in the morning and on the weekend, and that seasonal variation tracks changes in daylength.

Finally, chapter three examines how moral judgments about personal debt affect decisions by lenders about who to lend to and at what rate. By analyzing the text portion of loan applications in the microlending service Prosper.com, I show that, though traditional economic characteristics like credit score dominate, non-economic characteristics also help predict lending outcomes and have effects that are mediated by the creditworthiness of the applicant.

BIOGRAPHICAL SKETCH

Scott A. Golder was born in 1980 in Boston, Massachusetts and lived in Massachusetts continuously through his undergraduate and early graduate studies. From 1999 to 2003, Golder attended Harvard College, from which he graduated *magna cum laude* in Linguistics with a related field in Computer Science. While an undergraduate, he co-created the Harvard Dialect Survey, an online linguistic data collection project that was later featured in the New York Times and was its most-read article of 2013.^{1,2} From 2003 to 2005, Golder attended the Massachusetts Institute of Technology, completing an M.A. in Media Arts and Sciences at the Media Laboratory.

Golder has periodically worked in industry during his time as a graduate student. During his three years as a research scientist at Hewlett Packard Labs (2005-2008) in Palo Alto, California, Golder conducted among the first published studies of Facebook. He has also been a summer graduate intern at IBM Research, Microsoft Research New England, and Google.

Golder arrived at Cornell University in 2008 to pursue a Ph.D. in Sociology. He began a leave of absence in 2012 in order to pursue opportunities in industry, including working on a software startup, before completing his Ph.D. in 2017. He presently resides in Columbia, Maryland.

¹ <http://www.nytimes.com/interactive/2013/12/20/sunday-review/dialect-quiz-map.html>

² <http://www.theatlantic.com/technology/archive/2014/01/-em-the-new-york-times-em-most-popular-story-of-2013-was-not-an-article/283167/>

ACKNOWLEDGMENTS

First, I would like to thank my advisor and committee chair, Professor Michael Macy. Michael has been a consistent source of insights and enthusiasm throughout my time at Cornell, and my work has benefited from his guidance greatly. Our collaborations have been both productive and enjoyable, and I am grateful for his encouragement to seek impactful outlets in which to share them.

I would like to thank my committee members, Professor Victor Nee and Professor Jon Kleinberg. Victor kindly and generously provided several semesters of support and office space, enabling me to focus on my research, as well as untold hours of valuable and wide-ranging conversations. Jon's work has long been an inspirational example of how formal approaches can enlighten our understanding of social behavior; likewise, his advice and feedback have been valuable and appreciated.

I could not have chosen a better intellectual home than Cornell Sociology. An engaging community in which to learn and study, the department has also been supportive in accommodating my multi-year leave of absence, enabling me to both complete my graduation requirements and also pursue opportunities in industry.

Finally, I would like to thank my parents, Caroline and Stuart Golder, and my wife, Dr. Angie Boyce, for all of their support. My early-morning writing sessions have been possible only because Angie took on the bulk of the responsibility of getting our son Simon up, fed and off to daycare. Post-dissertation, I'm looking forward to having breakfast with them again.

TABLE OF CONTENTS

Biographical Sketch	iii
Acknowledgments	v
Table of Contents	vii
List of Figures	ix
List of Tables	xi
Introduction	1
Chapter 1: Digital Footprints: Opportunities and Challenges for Online Social Research	9
Chapter 2: Diurnal and Seasonal Mood Tracks Work, Sleep and Daylength Across Diverse Cultures	49
Chapter 3: Debt and Credit in an Online Microlending Market	79
Bibliography	136

LIST OF FIGURES

Figure 1. Hourly changes in individual affect broken down by day of the week. Each series shows mean affect (black lines) and 95% confidence interval (colored regions).	53
Figure 2. Hourly changes in between-individual affect (y-axis) over a 24-hour cycle (x-axis), broken down by day of the week. Each series shows the mean affect (black lines) and 95% confidence interval (colored regions).	54
Figure 3. Number of messages posted on Twitter (y-axis) by hour (x-axis) and day of the week.	55
Figure 4. Hourly changes in within-individual affect (y-axis) over a 24-hour cycle (x-axis), broken down by chronotype, for PA (top) and NA (bottom). Each series shows the mean affect (black lines) and 95% confidence interval (colored regions).	56
Figure 5. Hourly changes in individual affect in four English-speaking regions. Each series shows mean affect (black lines) and 95% confidence interval (colored regions).	57
Figure 6. Line of best fit through the 14.3M person-month observations (affect by minutes gained or lost per day). For visual reference, 100 aggregate observations binned by percentiles are superimposed.	58
Figure 7. English proficiency across the population. Left: Histogram of individual English proficiency in English-speaking countries shown in Figure 5. Middle: Histogram of individual English proficiency in all other countries. Right: Boxplots of English proficiency in each country/region.	75
Figure 8. A typical Prosper.com loan listing. This listing includes a photograph, detailed economic information (“Credit Profile”) and a borrower-provided free-text description of their reasons for borrowing and their other circumstances (“Description”). The list of bids received is shown at bottom.	96
Figure 9. Prosper’s weekly loan activity, March 2006 to September 2008.	100
Figure 10. Prosper bids disproportionately go to a very small number of listings, especially among the riskier credit grades.	101

Figure 11. Weekly investor demand, as measured by bid-to-listing ratio.	103
Figure 12. Proportion of listings (top) and loans(bottom) by credit grade and week.	104
Figure 13. Across all credit grades, nearly all loans are in good standing after three months. Over time, borrowers in riskier credit grades experience many more defaults.	105
Figure 14. A 2-D projection of the 64 dimensions produced by word2vec.	116
Figure 15. Partial dependence plots of debt-to-income ratio and loan amount requested.	124
Figure 16. Partial dependence plots showing the impact of selected LDA-derived topics on borrower rate.	130
Figure 17. Partial dependence plots showing the impact of selected LDA-derived topics on borrower rate, broken down by credit grade.	132

LIST OF TABLES

Table 1. Time zones and countries/regions.	62
Table 2. The overall dataset contains a large number of relatively inactive users whose aggregated messages include too little information to provide robust measures of individual affect. We excluded these users, as well as those who we identified as non-proficient in English.	77
Table 3. Counts of Activities on Prosper	100
Table 4. Count of Listings on Prosper by Number of Bids Received. Most listings received five or fewer bids.	101
Table 5. Prosper Group Membership Statistics	107
Table 6. Top words per topic generated using Latent Dirichlet Allocation.	113
Table 7. Regression model results, including economic inputs, photo presence and group membership.	117
Table 8. Performance of models learned using adaptive boosting	121
Table 9. Degradation in model performance relative to full model, when individual inputs are omitted	123
Table 10. Model performance by credit grade.	125
Table 11. Within-credit grade model performance relative to full model, when inputs are omitted	127
Table 12. Absolute and relative model performance when text analysis inputs are included.	128
Table 13. Absolute and relative model performance for borrower rate prediction, by credit grade (LDA model scores only).	128

INTRODUCTION

The activities through which we live our social lives have moved over the past quarter century from taking place exclusively offline, to taking place partially or mostly online, mediated through internet-based services and engaged with through a screen, either at one's computer or, increasingly, on one's mobile device. Furthermore, these tendencies feed on one another – the more time we spend in front of a screen, the more we engage in social activities that way; and in turn, the more social activities are centered on online experiences, the more we grow fixated to the screen. These online experiences may be as commonplace as sharing and socializing with friends or shopping for clothes and household goods, or may be as weighty as engaging in economic or political activity.

Delivering any of these services requires maintaining sufficient data to administer the services in question. A service for socializing with one's friends needs to maintain, for example, data indicating who is friends with whom, and an archive of their communications. An online merchant needs to remember who has purchased what, so that billing, shipping, and the other necessary activities of commerce may take place. In many cases, scaling a business entails scaling a large and expensive data infrastructure capable of tracking millions of users and potentially billions of interactions, in real time. It was not long before it became apparent that the data necessary to run a business could be repurposed in a variety of ways. A socializing service could not only track who is friends with whom, but also use that data to predict

who might be friends with whom. An online shopping site could use its understanding of who purchased what, to offer recommendations about what other things people might like to purchase. These new purposes are, broadly, of value to the user, and include assistance in locating old friends or in identifying the best product that meets one's needs and preferences.

As the capability to collect data grows, and with it the investments in learning to turn that data into information, the kinds of data that can be collected grow. Rather than tracking only those items a person purchases, for example, an online store might develop the data processing capability to track all those items a person looks at, as well as when, and from where (at home, on a mobile device, using a certain web browser, and so on.).³ The cycle repeats itself – greater learnings from data leads to greater investment in collecting, storing and processing that data, as well as to efforts to identify novel purposes to which the data can be put.

Like other technologies, the technologies of data analysis are not unambiguously or exclusively positive or negative in their effects, and can be put to uses that might not please users, for example encouraging or forcing them to reveal personal information they might otherwise not – even if that revelation is predictive or approximate, rather than explicit or definitive, and subjecting them to unwanted surveillance, marketing, discrimination, or even physical harm or the threat of it. Though this scenario sounds potentially dystopian, we may take comfort in the

³ The data from a single source can be combined with external data sources, as well; for example, in Chapter 2, data from the social network service Twitter is enriched by including geographic data in the form of global cities' latitudes and daylight hours.

possibility that the challenges we are forced to confront by pervasive data collection and aggregation can be addressed by the same. Though large-scale social networks may enable bad actors to threaten and harass from a distance, deeper understanding of the structure of those networks and the content of those messages may enable more effective filter creation or other technical mechanisms of inhibiting or stopping those bad actors. Though data enables potentially inappropriate quantification, for example using social behavior as a tool to guide access to economic or professional opportunities, as a society we are now forced to confront questions about whether we will support data being put to any purpose that benefits the holder, or whether we will circumscribe through law, regulation or norm those purposes that are unfair or unjust. And, as I explore in this dissertation, it is in large scale recordings of behavioral data that we might find the possibility of developing a greater understanding of many varieties of human behavior.

In recent years, a body of literature has started to develop in the social sciences exploring the “opportunities and challenges” (as I refer to them in Chapter 1) associated with these data and efforts by social, behavioral and computer scientists to learn from them.

One of the earliest critiques leveled at the use of online data for social science research had to do with representativeness. As I discuss in detail in Chapters 1 and 2, participants in online social spaces may not necessarily be representative samples of some greater population; this was especially true when internet use was limited to professionals and people affiliated with universities, but remains true today, in light of the differential access opportunities that split along predictable geographic, racial and

socioeconomic lines. However, it is not feasible to expect that online social spaces would be representative in this way, and it is not necessary that they do so, for the same reasons that laboratory experiments need not represent the population as a whole, so long as variation in the behaviors in question does not lie along the same axis as the population's non-representativeness. Though it has been shown that non-representative laboratory samples can have effects on what are believed erroneously to be fundamentally human rather than cultural attributes (Henrich, Heine, and Norenzayan 2010), laboratory experiments in general attempt to isolate single behaviors and induce variation in them that is expected to be robust against cultural or other idiosyncratic factors. Also, it is possible in some circumstances to examine both the universal and the culturally specific manifestations of some behaviors using online data, as demonstrated in Chapter 2, where I show how mood expression varies globally, but with attention to how culture mediates those expressions.

As noted in Chapter 1, and echoed by critical works by others, online data is necessarily incomplete and imperfect (Lewis 2015; McFarland, Lewis, and Goldberg 2016; Shaw 2015). This much, though, becomes obvious after even the most minimal introspection. Data from an online social environment provides information about communication *within that environment* and views into communication among that same set of actors taking place through other channels is necessarily absent. Studying workplace email networks, for example, provides one view onto how coworkers communicate, but tells us nothing about the conversations they have face-to-face, over real-time chat channels, or otherwise. Purchases people make in one online store provide a partial view onto their consumption patterns, revealing nothing about the

things they buy at other online stores or at their local shopping mall.

Data is also error-prone and incomplete or misleading in either obvious or non-obvious, and sometimes playfully meaningful ways. Out of laziness, fear, privacy or other motives, people may fill out profiles incompletely, including only those bare minimum facts that are required to participate in a service. They may not include their name, or their age, or their location or gender – the service might not even ask for it. When they do include information, they may use pseudonyms, say their age is 120 years old to avoid providing their real age, or list a fictional or incorrect location. Sometimes misinformation can be used to make a point – providing a politically controversial location may be a sign of solidarity with the people at that location, and also an attempt to confuse location based algorithms.

Activities like these are what Shaw (2015) points to as the historicity and “materiality” of an online social space, and suggests more generally that the architectural structure of an online environment and the behaviors it affords limit its use as an instrument of social scientific research. However, as I describe in Chapter 1, any online space should be thought of as much as an ethnographic field site as a source of disembodied data; it is incumbent upon the researcher to develop an understanding of the kinds of social activities that are expressed in an environment before implicitly bringing an interpretive lens to it, even if that lens is framed primarily in terms of the properties of the data the site generates. As Butts (2009) points out in the context of network analysis, choices about how to define which nodes count, and what constitutes an edge, can have large effects on the resulting understanding of behavior in a network. Likewise, a mischaracterization of the

meaning of a behavior in an online space can result in inaccurate conclusions, as has always been the case in field research in more traditional ethnographic work in sociology and anthropology.

These challenges, representativeness, completeness, and accuracy, are indeed important concerns, and demonstrations of why this is so stand as useful correctives against the view that mere data alone, at sufficient scale, renders them moot. The latter view is exemplified by *Wired* editor Chris Anderson's (2008) polemical article, "The End of Theory," and more recently and substantively, by a debate between Google AI researcher Peter Norvig and MIT linguist Noam Chomsky (Norvig 2011), whose distinct definitions of success yield distinct beliefs about what constitutes good science; as Breiman (2001) puts it, these two camps differ in whether it is most important that models are *accurate* or that they are *explanatory*. In brief, Chomsky argued that statistical models whose sole aim is to reduce the error on some prediction task are not scientific progress, because they do not increase our understanding of the mechanisms or structures giving rise to the data, while Norvig argues that statistical language models have value in a world in which reality is too complex to be explained by simple models, not to mention the success that has been shown in delivering technologies like search engines, speech recognition, machine translation.⁴ For Chomsky, a successful model of grammar would predict with high fidelity when a human speaker would deem a sentence ungrammatical, based on an understanding of the tree structure of that sentence; a statistical model might look at the same sentence

⁴ Statistical language models also provide social scientists with tools for coding and quantifying textual

and instead assign it a low probability, due to having never before seen a sentence that “looks like” it.

Both have a point. The statistical modeling community has yielded approaches to building predictive models that have demonstrable success in the real world, from language to computer vision, and these models, with potentially millions of inputs, do explain more of the variance in a dataset than a far more parsimonious model might, even when appropriately controlling for overfitting to the data at hand. What’s more, the traditional tools of science may not be up to the challenge of answering questions using large, modern datasets. Since the t statistic is dependent on the standard error, which in turn is dependent on n , for a sufficiently large dataset, any t statistic will be likewise large, yielding very small p values, which have long been the cornerstone of tests determining scientific importance (Krueger 2001). In other words, old rules of thumb for evaluating models no longer work, and in such a world, more appropriate evaluation may indeed include reduction of prediction error on unseen data.

On the other hand, parsimonious theoretical models’ goal is not to explain as much variance as possible, but rather to explain as much variance as possible using the combination of factors implied by a hypothesized mechanism about how the world works. For this reason, quantitative social scientists, in particular, have leaned toward a *theory-first* rather than a *data-first* approach; though a dataset may be intriguing because it suggests the possibility of testing a particular hypothesis, the hypothesis necessarily comes before the test. This contrasts with a *data-first* approach, in which,

data. Chapter 3 demonstrates the use of a number of these methods.

much like ethnographically-oriented social scientists, one might explore the data as though an anthropologist stumbling into a remote society or a natural scientist encountering a previously unobserved physical phenomenon, seeking to first observe patterns, which may raise other questions and suggest other tests to perform, or may provide evidence consistent or inconsistent with existing theories. For example, Chapter 2 brings to bear a large sample of data from Twitter which, through exploration, revealed patterns that informed existing theories about human mood that had previously been observed only with much smaller and less powerful datasets.

The relationship between the ethnographer and the statistical modeler shares more in common than a data-first approach. As Mohr and Bogdanov (2013) point out in a special issue of *Poetics* focused on topic modeling, the approach shares much in common with post-World War II work in content analysis, with the shared goal of identifying and quantifying themes in text, but in a faster and potentially more objective way. Topic modeling, as well as other text analysis methods, are employed in both Chapters 2 and 3, with methods ranging in sophistication from keyword counts to topic modeling, to semantic modeling.

Despite the challenges, both theoretical and practical, of working with large-scale behavioral data from the internet, the detailed observations of multifaceted human behavior that these systems provide will likely make them indispensable to the future of the social sciences. Taking advantage of these opportunities will depend on whether social scientists can collaborate with and learn from computer and information scientists to develop and employ the multiplicity of qualitative and quantitative methods necessary to make sense of that data and learn from it.

CHAPTER 1
DIGITAL FOOTPRINTS: OPPORTUNITIES AND CHALLENGES
FOR ONLINE SOCIAL RESEARCH⁵

Introduction

Scientific disciplines make revolutionary advances not only through new discoveries, theories, and paradigms, but also because of the invention of new tools and methodologies (Kuhn 1962). The electron microscope, space telescope, particle accelerator, and MRI have allowed scientists to observe the world at greater scale or at finer resolution, revealing previously-obscured details and unexpected patterns, and experiencing the "eureka moments" of scientific breakthroughs. Newly developed tools for observing online activity are having a similar transformative effect on the social and behavioral sciences. These studies show how "digital footprints" collected from social media enable us to understand human behavior and social interaction in ways we could not do before.

While the societal impact of electronic communication is widely recognized, its impact on social and behavioral science is also profound, providing global yet fine-grained observational data and a locus for population-scale experimentation. A 2001 Annual Review of the "social implications of the Internet" (DiMaggio et al. 2001) assessed the Internet as a transformational phenomenon in the reproduction of social inequality (Hargittai 2010; L. Robinson 2011), community mobilization (Hampton

⁵ A version of this chapter was published as Golder, S. and Macy, M. (2014) "Digital Footprints:

and Wellman 2003; Rainie and Wellman 2012) and the use of leisure time (J. P. Robinson 2011). This review turns the tables, surveying studies that use online data to advance knowledge in the social sciences. A 2004 Annual Review of the “new science of networks” surveyed recent advances in the mathematics of networks, including biological and mechanical as well as social systems (Watts 2004). Although network analysis is clearly an important application of online data, the transformative research opportunities opened up by new sources of empirical data include but also extend beyond network analysis. The rapidly growing field has become too large for a comprehensive review, and therefore only a limited number of studies that illustrate the theoretical and methodological opportunities and challenges are referenced here, with a slight bias toward papers authored by sociologists or published in sociological journals. Although I include studies that examine online purchases to study social behavior, I primarily focus on studies in which people interact directly with one another, such as social networking sites.

Hard Science

Over the past century, there has been no shortage of social theory but there are severe constraints on access to data. The reason is simple: social life is very hard to observe. For example, it is much easier to ask an isolated individual about their friends than to observe the ongoing interactions and exchanges that are the stuff of friendship. Ethnographic participant-observation studies and surveys of complete networks make it possible to fully document social interactions, but only at costs that can be

Opportunities and Challenges for Online Social Research.” *Annual Review of Sociology*, 40:129-152.

prohibitively expensive to implement except in very small groups. The need to collect relational data through direct contact has therefore generally limited studies of social interactions to small bounded groups such as clubs (Zachary 1977) and villages (Entwisle et al. 2007). Lengthy time-series data on nation-level populations, such as the Framingham Heart Study⁶ or The National Longitudinal Study of Adolescent Health (Harris et al. 2009) are enormously expensive logistical challenges and are usually undertaken by multiple cooperating institutions in government and academia. Attempts to measure network structure at the population level by surveying egocentric networks (a randomly chosen person and their network neighbors) can be useful for studying the attributes of network nodes (such as degree), and edges (such as tie strength), but this methodology has serious limitations (Flynn, Reagans, and Guillory 2010; Marsden 1990), including the inability to measure essential network attributes (e.g. distances, clustering, connectivity, and centrality) or social interactions (e.g. diffusion and polarization).

Because of the difficulty observing social interactions at population scale, most surveys rely on random samples composed of observations that are selected to be independent and to provide an unbiased representation of the underlying population distribution. However, independent observations preclude the ability to directly measure influence from a respondent's friends. We know that people do not entirely "think for themselves," but when we study opinion formation using random samples, we are left with little choice but to assume that a respondent's opinions are shaped

⁶ <http://www.framinghamheartstudy.org>

entirely by his or her other traits, such as demographic background, material self-interest, or personal experience. As a result, we cannot rule out the possibility that demographic differences in opinions (e.g. the social liberalism of college graduates) are spuriously generated or exaggerated by the unmeasured effects of peer influence (McPherson 2004; Della Posta, Shi, and Macy 2013; Salganik, Dodds, and Watts 2006). Conversely, snowball sampling makes it possible to obtain relational data among network neighbors with which to measure demographic differences in beliefs and behavior net of the similarity between network neighbors, but the path dependence in selecting respondents makes it more difficult to obtain an unbiased representation of the population distribution.

Longstanding limitations on the ability to observe social interaction are rapidly disappearing as people all over the globe are increasingly choosing to interact using devices that provide detailed relational records. Data from online social networks – email archives, phone logs, text messages, and social media postings – allow researchers to relax the atomistic assumptions that are imposed by reliance on random samples. In place of path analytic models of social life as relationships among variables that measure individual traits (Duncan 1966; Wright 1934), data from online social networks makes it possible to model social life as relationships among actors (Macy and Willer 2002).

The rapid increase in the use of digital technologies that generate time-stamped digital footprints of social interactions, from email (Kossinets and Watts 2006) to mobile telephone (Eagle, Macy, and Claxton 2010) to social media (Lewis et al. 2008), affords unprecedented opportunities for the collection of both experimental and

observational data on a scale that is at once massive and microscopic – massive in the sense that the people under study can number into the millions and the data grow into the terabytes, and microscopic in the sense that individual micro-interactions are recorded. In place of retrospective reports about respondents’ behavior and interactions, online data can provide a detailed record of daily activities and the frequency and intensity of social relationships. These methods greatly expand our ability to measure changes in behavior, not just opinion; to measure these changes at the individual level yet on a global scale; to observe the structure of the underlying social network in which these individuals are embedded; to travel back in time to track the lead-up to what later becomes an event of interest; and to find the dogs that don’t bark (e.g. the failed outcomes that escape the attention of publishers, editors, and authors).

This research strategy is not new. For many decades, social and behavioral scientists have acquired data collected as a byproduct of the administrative or record-keeping processes of governments and organizations. Organizations track their membership lists, firms track the purchases of customers and the performance of employees, and banks collect massive data from credit card transactions.

What is new is the macroscopic global scale and microscopic behavioral extensiveness of the data that is becoming available for social and behavioral science. The Web sees everything and forgets nothing. Each click and key-press resides in a data warehouse waiting to be mined for insights into behavior, to enable useful functions from spam detection to product recommendations to targeted advertising. Our mobile phones, tablets, and laptops report every webpage we visit and every link

we click and can even report our precise location and movements. Our social interactions are mediated through email, Skype, instant messaging, Facebook, and Twitter. Our photographs are identity-tagged, geo-tagged and time-stamped, creating a who-when-and-where recording of everything we upload. Social media platforms like Facebook and online labor markets like Amazon Mechanical Turk make it possible to conduct controlled experiments using thousands of participants from all over the world.

The emerging field of computational social science (Lazer et al. 2009) is concerned with computational methods to collect, manipulate and manage massive amounts of data, as well as with employing the appropriate techniques to derive inferences, such as automated content classification and topic modeling, natural language processing, simulation, and statistical models for analyzing non-independent observations (Anderson, Wasserman, and Crouch 1999). The rapid growth of computational social science reflects the growing recognition that these new tools can be used to address fundamental puzzles of social science, including the effects of status competition, trust, social influence, and network topology on the diffusion of information, the dynamics of public opinion, the mobilization of social movements, and the emergence of cooperation, coordination, and collaboration.

Computational social science has also reinvigorated social network analysis, one of the historical specialties in sociology that has long been concerned with understanding the processes behind the formation of social ties and their consequences for and constraints on the actions and efforts of individuals and entire communities. Until recently, social network analysis has been limited to very small groups by the

requirements of direct observation of interpersonal interactions. We now have the ability to obtain detailed measures of network structure and network processes at the population level. The challenge of analyzing massive amounts of online data has pushed social network analysis into the forefront of computational social science, as these techniques have been applied to the inherently relational data created from online interaction.

When it Rains it Pours

The Social Telescope

The ability to observe hundreds of millions of people makes it possible to measure differences with small effect sizes that might otherwise be swamped by random variability. Just as an enormous antenna like the Arecibo Observatory is required to detect the low frequency radiation emitted from neutron stars (Lovelace & Tyler 2012), online networks comprise a massive antenna for social science that makes visible both the very large, e.g. global patterns of communication densities between countries (State et al. 2012) and the very small, e.g. hourly changes in emotional affect and micro-behaviors like doing homework, getting drunk, and getting a headache (Golder and Macy 2011).⁷

Online behavior is recorded in real-time rather than retrospectively. In social network studies, when individuals are given "name generators" and surveyed about their communication patterns, they are subject to a variety of potential biases. Question wording and ordering can cause respondents to artificially limit or otherwise

⁷ The associated website timeu.se (<http://timeu.se/>) provided an interactive tool for plotting the

vary the individuals they report, leading to underestimates of network size (Fischer 2009; Pustejovsky and Spillane 2009) or even measures of some other network (Burt 1997) when survey questions mistakenly elicit report of a social tie outside the researcher's intended scope. Online behavior – time-stamped and passively recorded – provides an unambiguous recording of when, and with whom, each individual communicated.

When activities are recorded via mobile devices, real-time mosaic accounts of collective behavior become possible that otherwise could not be reconstructed. As smartphone use increases in prevalence, the offline context of online behavior becomes available, such as common participation in a public event. For example, sampling a corpus of tweets (brief messages posted on Twitter) that occurred during a certain time range, and within a limited radius of a given event, can reconstruct how online activity complemented a parade or demonstration, or add a geographic variable back into an analysis that is otherwise blind to spatial location.

Relatedly, online behavior is observed unobtrusively, limiting the potential for Hawthorne-type effects in which researcher-induced desirability bias makes it difficult to observe normatively inappropriate behaviors (e.g. expressions of racial and ethnic prejudice), which participants may self-censor in surveys and in laboratory studies (Zizzo 2010). Observing behavior unobtrusively ensures that the social pressures and normative constraints on individuals are exerted by their peers rather than by the researchers. For example, online dating sites provide an unprecedented opportunity to

prevalence of keywords over the course of the day and week.

study the effects of racial and ethnic preferences on mate selection choices. Using a sample of 6,000 online profiles from Yahoo! personals, Robnett and Feliciano (Feliciano, Robnett, and Komaie 2009; Robnett and Feliciano 2011) found that, among those Whites who stated racial preferences in their online profiles, men were more likely to exclude Blacks than other racial categories, while women were more likely to exclude Asians. Similar results were reported by the online dating site OK Cupid⁸ which showed that Black women received replies at lower rates, and women of several races preferred White men over men of other races. In another dating-related study, Taylor et al. (2011) found support for the “matching hypothesis” that people seek partners whose perceived social desirability matches their own self-assessment.

Moreover, online interactions have been characterized as "persistent conversations" (Erickson 1999) that can be observed in real-time, even if the observation is taking place after the fact. Unlike ephemeral in-person conversations, online conversations are recorded with perfect fidelity and can persist forever. Though care must be taken when analyzing documentary evidence out of its original historical context, long after perspectives and circumstances have changed, the conversations themselves can be largely reconstructed, allowing retrospective analyses to be far more complete and exact than in most archival research.

The task for the researcher is to see online behavior as social behavior, the kind that might occur in any field site, be it a remote village, a law office, or a high school cafeteria. Some researchers explicitly conceptualize online sites as field sites in the

⁸ <http://blog.okcupid.com/>

ethnographic sense (Lyman and Wakeford 1999). Relatedly, online behavior in social media represent social action in the Weberian sense – action that is oriented toward others (Weber 1922), involving what Weber called “verstehen” – the subjective meaning for the actors involved. Paccagnella (1997) noted the multiple ways one might interpret the purpose, use, and limitations of technology, hence the need not to conflate the meaning to the researcher with the meaning for users (Pinch and Bijker 1984).

The Virtual Laboratory

Although most research using online data has been observational, a growing number of studies use the Web as a virtual lab for controlled experiments. Experiments address a key limitation of all observational studies, online or off – the inability to measure a phenomenon free from potentially confounding unmeasured factors. For example, it has been difficult to distinguish between contagion on a social network and common exposure of network neighbors to some unobserved source of similarity. An outbreak of sneezing, for example, could indicate a spreading virus or common exposure to seasonal allergens. Aral, Muchnik, and Sundararajan (2009) reviewed numerous statistical techniques that have been proposed to tease these processes apart using observational data and concluded that none are sufficient, a conclusion also reached by Shalizi and Thomas (2011).

Controlled experiments with random assignment are one solution. In a path-breaking pair of studies, Centola (2010, 2011) created a web-based health information community that made it possible to manipulate the levels of clustering and homophily in users' social networks. By randomly assigning participants to conditions, Centola

removed shared environment and homophily as sources of network autocorrelation, leaving only the possibility for contagion as an explanation. He found that the rate and extent of contagion was higher in the clustering condition than in the random condition (2010), consistent with the predictions of theoretical models (Centola and Macy 2007) of the spread of simple and complex contagions on small-world networks in which complex contagions benefit from the social reinforcement provided when multiple neighbors become “infected.” This social reinforcement is more likely when the network is highly clustered. Adoption was also greater in the homophilous condition (2011) than in the random condition, with no variation in network structure.

Experimentation online offers several advantages as well as challenges compared to traditional offline experiments in laboratory settings. An obvious advantage is the greater economy of scale. For example, Centola’s online experiment with repeated involvement of 144 participants would be logistically prohibitive in the lab, but once an online system is built for a few users, the marginal cost of scaling it up to hundreds or even thousands of users is relatively minimal. Larger numbers of participants not only increases statistical power, it also allows new research opportunities. For example, it becomes possible to test hypotheses about changes in collective behavior, in which groups rather than individuals are the units of analysis.

Less obvious but arguably more important theoretically, scalable experiments allow multiple simultaneous realizations of the same starting conditions. This makes it possible to test the possibility that highly non-random patterns may nevertheless have very limited predictive value if the patterns observed in one “world” vary widely (and perhaps entirely randomly) from one world to the next, due to processes that are path

dependent or confer cumulative advantage. This possibility was demonstrated for the first time by Salganik and colleagues (Salganik et al. 2006; Salganik and Watts 2009) in an experiment that has become an “instant classic.” They varied the level of social influence on a music download site that they created for the research. When participants were subject to influence, they found that music preferences were highly non-random in each world, making it possible to predict what would be downloaded simply by knowing how many others in that world had downloaded the same song. The surprising result was that this information was not very helpful for predicting what songs would be downloaded in another “world.” Their findings are a telling reminder to academic researchers, marketing departments, campaign managers, and epidemiologists who use observational data obtained from the one world that we inhabit to try to predict outcomes based on statistically significant patterns (Watts 2012).

Other online experiments have used existing websites rather than creating their own. Bond et al. (2012) tested the effects of social influence on voter turnout by manipulating whether Facebook users were exposed to information about the number of their friends who had voted. Although this experiment required the cooperation of Facebook, that possibility is reinforced by the widespread use of online experiments by industry. Web practitioners are already familiar with "A/B testing," in which multiple versions ("A" and "B") of a website are created and visitors are randomly assigned to one version or another to test the effects of different layouts, colors, or content on user engagement, retention, click-throughs, and so on. In many cases, studies motivated by theoretical questions can piggyback on the practical needs of

industry to better understand user behavior.

Researchers conducting otherwise traditional laboratory studies may now turn to an online labor pool. Amazon's "Mechanical Turk" is an online labor market with a vast global user base that is culturally, geographically, and demographically far more diverse than the undergraduate psychology majors that comprise most offline participant pools. Touted as "artificial intelligence," Mechanical Turk is designed to be a programmatic means of having humans complete tasks for which artificial intelligence is inferior, such as summarizing a document or choosing the best of five photographs. Typical compensation per task ranges from a few cents to a dollar, depending on the time required. Mason and Suri (2011) provide a review of methodological issues arising in the use of Mechanical Turk for online experiments. Rand (2012) points to a number of inherent limitations in nearly all online experiments, such as the inability to maintain consistency in and control over participants' immediate physical surroundings, with the associated risk that results may be contaminated by distractions or by outside sources of information. Additionally, "Turkers" sometimes click mindlessly simply to complete the task, which requires steps to detect random clicking and failure to follow instructions. Incentives may also not operate as intended, since Turkers appear to "anchor" on payment levels so that paying more makes them believe they deserve more, producing a greater quantity of work but not at a greater level of quality (Mason and Watts 2009).

Research Applications

Social Networks, Contagion, And Diffusion

Social network analyses have been among the earliest studies to use online data. Though numerous social networking sites exist, researchers have focused on two of the largest, Twitter and Facebook, with over 300 million and 1 billion worldwide users, respectively. Facebook profiles contain rich demographic data, including full names, dates of birth, geo-location, affiliations with friends, organizations, and political and social movements, and cultural tastes. Though less demographically rich, Twitter data is much easier to obtain via a more open API (see "Methods, Skills, and Training," below). Private data from Facebook is not generally available for research purposes, though several strategies exist for researchers to use Facebook data. First, researchers may build "apps" or add-on applications, which, when adopted by users, allow access to their demographic and behavioral data. These apps can be narrowly targeted to just those users with the desired demographic traits, network properties, or cultural or political preferences. However researchers need to keep in mind that reliance on self-selection means that the result is a non-random convenience sample whose results cannot be generalized even to the targeted sub-population. Second, researchers may invite participants into the lab the way they might for any other lab experiment, who then log in to their Facebook account (Gilbert and Karahalios 2009). Several studies have leveraged a Facebook policy that allowed people affiliated with the same university to see a more detailed user profile than is otherwise generally available (Lewis et al. 2008; Lewis, Gonzalez, and Kaufman 2011; Wimmer and Lewis 2010). These studies examined a complete university cohort to study homophily

patterns in race as well as cultural tastes.

Some researchers have arranged with Facebook staff to gain access to anonymized private user data for research purposes. For example, Golder, Wilkinson, and Huberman (2007) showed that private messaging by non-friends took place primarily at late-night hours, Traud et al. (2010) compared the network structures of multiple universities, and Mayer and Puller (2008) modeled tie formation within one university. Some researchers have collaborated with Facebook's own internal research team to analyze private data as well as conduct large-scale experiments. Das and Kramer (2013) examined inhibition in self-expression, but this was only possible because of the internal logging that takes place on messages that users write but ultimately choose not to post. Bond et al. (2012) isolated the effects of social influence from mass-media influence in increasing likelihood to vote, by conducting a massive experiment on 61M Facebook users.

boyd and Ellison (2007) identified distinctive structural aspects of social networking sites: a personal profile and a publicly-visible list of network neighbors (who share a tie). They note that the visibility of others' egocentric networks varies by site and as the sites themselves change over time. For example, LinkedIn makes some profile aspects visible only to paid users (viewer and viewed). Twitter allows users to view indirectly the content received by those they follow only if the user also follows those same people.⁹ Facebook requires symmetric social ties (two friends must each

⁹ That is, if A follows B, then A can see all of B's messages, but if B and C engage in a conversation, this is visible to A only if he follows both B and C. The purpose of this ostensibly due more to preventing cluttering A's message stream with irrelevant conversations than to protect the privacy of B

indicated friendship with the other) while Twitter and most blogging platforms allow asymmetric ties, leading to an extremely long-tailed degree distribution (e.g. celebrities often have many thousands of followers). Some demand a clear tie to one's offline identity (e.g. Google Plus and Facebook), while most do not, though even among the latter, participants often choose to establish a verified identity, especially on blogs and online dating sites where credibility is needed. These varying requirements impact users' behavior, helping some spaces to flourish and elicit trust and cooperation, while others exhibit distrust and hostility. These differences in turn open up important research opportunities for understanding how variations in structure, norms, cultural protocols, and incentives affect individual and collective outcomes.

Borgatti and Halgin (2011) distinguish two types of network ties based on their persistence over time – states (e.g. kinship and friendship) and events (e.g. exchanges and conversations). A further distinction can be made between ties of affiliation (e.g. participation in the same event) and interactions (e.g. discussing the event). Ties can also be positively signed (attraction, friendship, cooperation) or negative (repulsion, antipathy, conflict), and they can be directed (listening, liking) or undirected (marriage, kinship, partnership). Online social networks share these properties. Leskovec, Huttenlocher, and Kleinberg (2010) examined tie formation in online networks including Epinions, Slashdot, and Wikipedia and found that undirected ties are formed as predicted by structural balance theory (the product of signs in a

and C's conversation.

balanced triad must be positive), but when ties are directed, status effects appear to play the larger role (e.g. if A defers to B and B defers to C, C is unlikely to defer to A).

A number of studies have used online networks to confirm two classic findings on the importance of ties that span large network distances, Granovetter's (1973) Strength of Weak Ties and Burt's (1992) Structural Holes. For example, Eagle et al. (2010) used national telephone logs among 65M subscribers (about 90% of the population) to show that diversity in the networks of the members of a community was positively related to economic development, confirming offline network results reported by Granovetter and by Burt. Gilbert and Karahalios (2009) studied the relationship between tie strength and connectivity using data from Facebook. They employed an innovative approach to developing a metric for online tie strength. While studies often rely on the number of messages exchanged as a metric for tie strength, Gilbert and Karahalios used multiple indicators, including exchange of photos and public and private messages. In their lab study, they instrumented a Web browser to collect participants' Facebook activity and compared this to participants' ratings of the strength of their ties to various friends. A similar study compared the volume and direction of messages, retweets, and @mentions among Twitter followers with the same users' offline friends and discovered a close correspondence (Xie et al. 2012).

Other research has replicated Milgram's classic investigation of the small-world phenomenon in which letters traveled through the mail through a chain of acquaintances until a target unknown to the originator was reached, which revealed the celebrated "six degrees of separation" (Milgram 1967; Travers and Milgram 1969).

Dodds, Muhamad, and Watts (2003) found a similar average path length in an experimental study of search on global email networks, and Leskovec and Horvitz (2008), using a global instant messenger network of 240M users, observed a mean path length of 6.6 steps, compared to Milgram's 5.2. A similar analysis of the global Facebook network (Ugander et al. 2011) found that number of steps separating users had declined from 5.3 in 2008 to 4.7 in 2011 as the network grew in size.

Massive network data have also made it possible to study how structural conditions affect the spread of social contagions, including the decision to join a group, adopt a convention, or spread information. Bakshy et al. (2012) used news feed posts for 250M Facebook users to show that novel information spread primarily through weak ties. In contrast, using mobile phone call records for 4.6M subscribers (about 20% of the national population), Onnela et al. (2007) found that while weak ties "held the network together" (in that disconnection of the network into isolated components was most vulnerable to deletion of these ties), most information traveled through ties of intermediate strength. The authors conclude that models of network structure typically rely on global characteristics such as betweenness, implicitly weighting all ties equivalently, but tie strength may play a larger role than the global characteristics.

Backstrom et al. (2006) investigated social influence in two social networks, LiveJournal (an online blogging community) and DBLP (a database of academic paper coauthors). The offline co-authorship network differs from the online blogging community in requiring far greater personal interaction and coordination. Nevertheless, the likelihood of joining a community (on LiveJournal) and attending a

conference (evidenced by DBLP) both increased not only with the number of network neighbors who had joined, but more surprisingly, with the number of closed triads among these neighbors. A possible explanation is that the ties between two neighbors are stronger when the triad is closed (the two neighbors of an actor are also neighbors of each other, as found by van der Leij and Goyal (2011)). In addition, closed triads may entail greater fear of exclusion and more closely synchronized communications, leading to stronger social influence than when the triad is open.

Ugander et al. (2012), using Facebook-internal data about users' and non-users' email addresses, investigated how the probability to accept an invitation changed with the number of Facebook neighbors and the number of “connected components” (connected only by links through ego). Contrary to the result reported by Backstrom et al. (2006), the authors found that the probability increased not with the number of Facebook neighbors but with the number of connected components, even after controlling for demographic diversity. A possible explanation is that invitees discount multiple invitations from friends who know one another, interpreting these invitations as conveying redundant information about the benefits of membership. Since the data are missing two potentially important social ties, Facebook friends who did not include ego in their contact lists and friends who are not on Facebook, there is no way to know if distinct “connected components” in the observed ego network might actually be connected by these missing links.

Romero, Meeder, and Kleinberg (2011) found evidence to support the theory of complex contagions (Centola and Macy 2007) by examining the spread of the use of Twitter hashtags. Hashtags for controversial topics like politics were more likely to

be adopted following exposure to multiple adopting neighbors, compared to topics like music or sports. More recently, Weng, Menczer, and Ahn (2013) used Twitter hashtags to confirm a key implication of the theory of complex contagions – that the spread of complex contagions depends on network structure, a result that is consistent with the experimental findings reported by Centola (noted above). Other studies have used online data to test longstanding theories about information diffusion, including the existence of well-connected “influentials” who initiate cascades. Popularized by Gladwell (2000) in *The Tipping Point*, the theory of these high-degree network nodes (or “hubs”) was earlier proposed by Katz and Lazarsfeld (1955), who referred to them as “opinion leaders” in a two-step model of the flow of influence. Billions of advertising dollars are targeted at so-called influentials based on this theory, but a growing number of studies cast serious doubts. Dodds et al. (2003) found that successfully-completed chains in their replication of Milgram's “six degrees” study did not in fact leverage highly-connected hubs. Cha et al.'s (2010) study of 1.7B tweets found that hubs “are not necessarily influential in terms of spawning retweets or mentions,” a result consistent with Kwak et al. (2010) that also casts doubt on the influence of widely-followed users on Twitter. Similarly, Bakshy et al. (2011) identify cases in which actors with average degree are the source, and González-Bailón et al. (2011) point to the importance of random seeds as well as nodes with higher centrality.

Exchange, Cooperation and Trust

A growing number of studies are using online data to address enduring problems of trust and cooperation in social exchange, in which the valued goods being

exchanged are time, attention, information, and status. Research by State et al. (2012) is consistent with a basic principle of exchange theory (Homans 1961; Emerson 1962; 1972), that exchange relations tend to be reciprocally balanced. They found that “couchsurfers” (people who are part of an online community of budget travelers who stay in others' homes), compensate their hosts' hospitality by conferring status in the form of public comments.

Attention is also a valued resource in social exchange. Podolny (2001) suggests that attention is a prism or lens through which one is judged by others; having the attention of powerful others can, in turn, redound to one's financial benefit and is a signal to others about who is worth investing attention. Online experiments confirm that individuals are willing to exchange monetary compensation for praise and attention from peers, even when it is artificial (Huberman, Lock, and Onculer 2004). More broadly, Huberman's research program centering on the “attention economy” created by online interactions addresses the puzzle created by the sheer volume of information available online, which makes attention scarce and valuable. Yet little is known about how attention is directed or attracted. Twitter users have been shown, for example, to rate others as more interesting to the extent that their own neighbors expressed interest in those others (Golder and Yardi 2010).

Like attention, trust is another resource that can be especially important in online interactions where identities can be ephemeral, limiting the reliability of reputational information and the ability to punish cheaters (Friedman and Resnick 2001). In response, users have evolved norms to regulate behavior, such as requiring newcomers to a community to be first to commit to the exchange. In a pioneering

study of online interactions, Kollock (1999) observed this practice in a community of bootleg tape recording traders, who also collectively paid enforcement costs by maintaining a "blacklist" of people who should not be traded with due to perceived past transgressions. Other studies have confirmed a principle originally proposed by Hechter (1988) that it is more effective to reward trustworthy behavior than to punish transgressions, since the latter creates incentives to increase the costs of detection. Friedman and Resnick (2001) attribute the remarkable effectiveness of the eBay feedback system in part to the incentives the system creates to maintain one's identity, an incentive that increases over time.

Exchange-theoretic analysis can also be applied to personal as well as business and organizational relationships. For example Backstrom and Kleinberg (2014) randomly selected 1.3 million adult Facebook users to test the effect of network embeddedness (defined as the overlap in their friendship circles) on the formation and durability of romantic relationships. Surprisingly, they found that "dispersion" (or lack of overlap), not embeddedness, was conducive to successful relationships, a result that contradicts the theory of the strength of embedded ties but is consistent with a previously unexplored romantic implication of Burt's (1992) hypothesis that people are attracted to "structural holes."

Online research on social exchange includes survey research as well as observational studies. Willer et al. (2012) administered surveys on Freecycle and Craigslist to compare the levels of solidarity reported by the sites' respective members. The results confirmed the exchange-theoretic hypothesis that the generalized exchange of Freecycle entails greater levels of solidarity than the negotiated exchange taking

place on Craigslist.

Collective Action and Social Movements

Many online communities rely on voluntary contributions by large numbers of unrelated individuals, presenting researchers with a remarkable opportunity to address longstanding puzzles in the study of collective action: how do order and consensus emerge among loosely-affiliated contributors, and what motivates them to contribute to this public good? Two prominent examples are open-source task groups like Wikipedia and Linux and massively-multiplayer online games such as World of Warcraft and Everquest. An overview of these two areas is provided by Contractor (2013). Wikipedia is an openly-editable collaborative encyclopedia written and edited by thousands of volunteers every day. Like many voluntary associations in the offline world, Wikipedia, Usenet, and many other online communities, are self-governed almost entirely by the evolving normative obligations and limits collectively established and agreed to by their participants, but with the critical difference that the detailed evolutionary records are preserved for study by the scientific community.

As Wikipedia has grown, its community of editors has created a number of policies to guide contributors and to resolve disputes, such as policies requiring articles to be written from a neutral point of view and to include statements only if they can be supported by reference to a publicly-available source (not first-hand research by the editor) (Kriplean et al. 2007; Kriplean, Beschastnikh, and McDonald 2008). Although these institutional arrangements help to regulate and coordinate user behavior, they also make the motivation to contribute even more puzzling since there is less opportunity to exploit the community to promote a parochial point of view.

Anthony, Smith, and Williamson (2009) examined the quality of Wikipedians' contributions and pose the interesting puzzle that "anonymous Good Samaritans" contributed among the highest-quality content, while others (Welser et al. 2011) point out that Wikipedians self-organize into roles, focusing on "cleaning up vandalism," providing domain expertise, and so on.

Many of the challenges faced by formal organizations – recruiting a skilled labor force, defining roles and responsibilities, and monitoring and rewarding performance, also arise in massively-multiplayer online roleplaying games (MMORPGs). Players can take on a particular role (trolls, warriors, etc.) and they can unite to form guilds (teams), work together to attack other guilds, and perform in-game tasks such as achieving quests. Like Wikipedia, guilds must overcome collective action and coordination problems in order to select, train and retain members. Choi et al. (2008) found that good fit between persons and tasks is associated with longer membership in a guild, while Wang, et al. (2011) found that players' orientation toward performance and achievement displayed greater expertise, while those oriented toward having an immersive experience displayed less expertise.

To date, most of the research on these communities has been largely descriptive, and a vast opportunity remains for researchers to use data from user interactions to test hypotheses derived from the collective action, public goods, and game theoretic literature. Data from Wikipedia is freely available for download¹⁰ and Sony has made Everquest data available for academic research.

¹⁰ http://en.wikipedia.org/wiki/Wikipedia:Database_download

Collective action and social movement mobilization have also been studied using data from social media, particularly Twitter and Facebook. For example, data from Twitter has been used to provide digital traces of the spread of protest information and public sentiment in the Arab Spring (González-Bailón et al. 2011). Because information about protests reaches people through numerous channels besides social media, it is impossible to isolate the effects of social media net of other channels. However, users' messages can be used to measure the rate and extent of mobilization by tracking topic changes in user-generated content at a very fine-grained temporal level, and these changes can in turn be correlated with changes in the users' social and spatial environment as reflected in news accounts as well as the content of other users. For example, Weber, Garimella, and Batayneh (2013) track secular vs. Islamist postings by Egyptian Twitter users over the course of the Arab Spring.

Researchers have also used changes in the distribution of user-generated content to not only explain political outcomes but to try to predict them. For example Digrazia et al. (2013) showed that local US election outcomes were positively correlated with the number of times that Republicans had been mentioned in tweets. Nevertheless, a review of recent papers (Gayo-Avello 2012) concluded that predictive claims are exaggerated. One important limitation on predictive power is that users of social media are not randomly selected in the way that is possible with survey research. Users preferentially choose to follow sources that conform to their existing worldviews (Sunstein 2001) and preferentially rebroadcast ("retweet") conforming messages, as well (Conover et al. 2011). Boutyline and Willer (2011) showed that there is a valence effect to the formation of so-called "echo chambers" – those farther

to the political right exhibited more ideological homophily in who they chose to follow on Twitter.

Krebs (2008) took a different approach to analyze the red-blue divide using online data. Krebs constructed a social network of the top 100 political books sold on Amazon in three time-periods, 2003, 2004, and 2008. The network edges corresponded to co-purchases ("customers who bought this book also bought ____"). In each year, almost all of the political books were tightly grouped into "red" and "blue" clusters, with only one or two books (e.g. *Ghost Wars* and *Rise of the Vulcans*) linking the two camps. This result is consistent with red-blue ideological clustering reported by Adamic and Glance (2005) using data collected from blogs during the 2004 US electoral cycle.

These studies show that the use of social media to study opinion dynamics provides a potentially important complement to – not substitute for – traditional survey methods. Each can be used to obtain information that is missing in the other. Surveys provide more reliable estimates of the distribution of opinion in the underlying population but typically provide only retrospective responses and lack network data with which to study the flow, diffusion, and clustering of opinion.

Challenges

The Privacy Paradox

These new data confront researchers with imposing hurdles, ranging from validity of both the data and how it is sampled to the ethical issues regarding its use. Online data presents a paradox in the protection of privacy: data is at once too revealing and not revealing enough. On one hand, online data often lacks the detailed

demographic profile information that is standard in survey research. For example, while Twitter data are public, many users provide sparse, invented, incomplete or ambiguous profile information, making it difficult for researchers to associate the content of tweets or the attributes of network nodes with basic demographic measures like age, gender, ethnicity, or location. Identity is slippery and poorly defined in some online communities where participants are known only by a self-chosen username that they may change at any time. In some cases, it is difficult to tell who is a human; the growing incidence of "spam accounts" is worrisome, and despite progress in spam detection methods (Yardi et al. 2010), spammers manage to keep the arms race going. As spammers become more sophisticated, it becomes harder for social scientists to clean the data they collect without specialized technical training, a problem explored in more detail below.

Nevertheless, rapid progress is being made to address these limitations. For example, Compton et al. (2013) showed how label-propagation algorithms can be adapted to potentially geo-locate the vast majority of Twitter users to within a few kilometers, and Jernigan and Mistree (2009) showed how Facebook content can be used to infer a wide range of user attributes, including age, gender, sexual preference, and political party affiliation. These advances illustrate the other side of the dilemma – that online data may not be private enough. These new sources of data raise challenging procedural, legal, and ethical questions about how to protect individual privacy that are beyond the scope of this review, but there is a growing body of research showing that anonymizing or encrypting data is not sufficient for protecting privacy, as this can sometimes be reverse engineered (Backstrom, Dwork, and

Kleinberg 2007; de Montjoye et al. 2013) using the unique attributes of individuals' egocentric networks or physical mobility patterns.

Access to private data can be a significant challenge. Most online data is owned by private corporate entities who may restrict access in large part because of concern to protect the privacy of their subscribers. These restrictions have raised concerns about reproducibility of results, corporate influence, and stratification in the research community between a small elite that is well-connected to social media companies and everyone else (boyd & Crawford 2011, Huberman 2012). New protocols and institutional arrangements are needed to align the goals and needs of industry and the academic community. Online companies compete aggressively to attract academic talent (including social scientists) and several companies maintain “university relations” departments who can help to facilitate research collaboration. In addition, advanced programming and other technical skills are required to access and process large semi-structured data sets, as described in more detail below.

Measurement Issues

Although advances in identifying sentiment and opinion from text are proceeding rapidly (Pang and Lee 2008), we can only measure inner states indirectly, through their behavioral expression. For example, psychological lexicons (Pennebaker, Francis, and Booth 2001) can be used to measure the expression of affective rhythms on a global scale (Golder and Macy 2011), but these methods cannot account for temporal lags between expression and experience. Moreover, asynchronous communication allows users to introspect and revise what they write, such that what appears to be spontaneous expressions of an underlying mental state

may instead be self-censored and deliberate (Das and Kramer 2013).

As noted above, an important limitation in all observational studies of network contagion, whether online or offline, is the difficulty distinguishing between homophily and contagion. Homophily refers to a variety of selection mechanisms by which a social tie is more likely between individuals with similar attributes and environmental exposures (McPherson, Smith-Lovin, and Cook 2001). Contagion refers to influence mechanisms (e.g. imitation or peer pressure) by which traits diffuse along network edges. Homophily and contagion offer competing explanations for network autocorrelation, which refers to the greater similarity in the attributes of closely connected nodes. Based on simulated networks, Shalizi and Thomas (2011) conclude that “there is just no way to separate selection from influence observationally” (see also Manski 1993). This does not mean that observational studies using online networks are useless, but researchers need to refrain from assuming that the observed network autocorrelation reflects contagion effects and to acknowledge that the similarity between adjacent nodes may reflect the mutually reinforcing effects of influence and selection whose separate contributions may be impossible to tease apart. For example, although Ugander et al. (2012) controlled for demographic similarity (sex, age, and nationality), there are countless other ways in which shared environments, affiliations, interests, and personality traits might cause two friends to join Facebook independently but not on the same day, making it look like the “early adopter” influenced the friend they invited who would have joined anyway.

One solution is to conduct controlled experiments that manipulate exposure to

a possible contagion, as in the Facebook experiment by Bond et al. (2012) noted above. Where experimental methods are not feasible and the only data are observational, researchers can tease apart influence and selection by using an instrumental variable that is correlated with alter's exposure to the contagion but not to ego's and then comparing the presence of the contagion among ego's with and without exposed alters (Imbens and Angrist 1994).

Another fundamental problem in online as well as offline network studies is deciding what constitutes a social tie (Butts 2009). In survey-based research on ego networks, controversy has centered on how to ask respondents to nominate a friend. In studies of online communication networks based on telephone logs, email traffic, or Twitter messages, a key question is how to determine the type and number of exchanges (e.g. emails or wall postings) that are necessary to indicate the existence of an enduring social relationship (Borgatti and Halgin 2011). For example, in their network analysis of UK telephone logs, Eagle et al. (2010) required at least one call in each direction, which is the most widely used threshold in studies that use communication data to identify social networks. Other studies have examined robustness and changes of results across a range of thresholds (Adamic and Adar 2005; De Choudhury et al. 2010; Romero et al. 2011). Studies using Twitter data face the additional question of whether to use follower relations (in which two users each follow the other), "@mentions" in which two users refer/reply to each other (Honeycutt and Herring 2009), or retweets in which two users each repost what the other has written (boyd, Golder, and Lotan 2010; Conover et al. 2011).

A related issue is whether the metric for establishing a link is consonant with

the actors' conception of a social relationship. These questions arise as well in studies of offline networks, particularly affiliation networks, for which a number of heuristics have been proposed to determine whether the edge corresponds to an actual interaction, such as similarity (Flynn et al. 2010), regularity of structure and kinship terms (Brashears 2013), and indications of instrumental vs. sentimental ties (Freeman 1992). One study of Twitter networks confirmed that follower relations do not correspond to offline friendships. However, they developed new algorithms that detect offline friendships using a novel measure of user closeness (Xie et al. 2012).

A similar issue arises in deciding where to set the threshold for which users to include in the analysis, given that active participation in online environments is often highly skewed (Preece and Shneiderman 2009). Low-activity users may not represent committed members, but arbitrary thresholds may also have the effect of artificially excluding a large number, even a majority, of individuals from the analysis, with potentially misleading effects on network measures like density, degree distribution, and mean path length.

Is the Online World a Parallel Universe?

Researchers also face the challenge of generalizing from online to offline behavior. Interactions offline differ in important and obvious ways from those online, including the lifting of geographic and temporal constraints of face-to-face communication. For example, the ability to wait to answer an email or text message or respond to a status update affords the opportunity to introspect and be more deliberate and strategic about one's self-presentation (Goffman 1959). The anonymity permitted by some online platforms frees users to invent an entirely new persona, raising doubts

about the credibility of demographic profile data. Anonymity can also permit or encourage the production of the vitriolic speech that pervades many online conversations but is generally unthinkable offline. Differences between online and offline modes of communication have been the subject of a number of studies focusing on their comparative "richness," or the bandwidth available for the transmission of verbal and visual cues (Daft and Lengel 1986; Walther 2007). Although face-to-face interaction is richer visually, there are other aspects of online communication that can be much denser than their offline counterparts, such as the ready availability of persistent histories (Hollan and Stornetta 1992) and the opportunity to craft novel modes of expression such as the emoticon or Twitter "@reply" (Herring 1999; Honeycutt and Herring 2009; Menchik and Tian 2008).

Early studies also raised questions about possible distorting effects of online access. The "displacement" theory posited that Internet use was an asocial activity that took time away from family and friends (Nie and Hillygus 2002), and empirical research showed that these effects varied, depending on the type of online activity (Kraut and Kiesler 2003). However, this research predates the "social media" era, and more recent research (J. P. Robinson 2011) suggests that the displacement theory is less relevant today .

The "digital divide" raises additional concerns about generalizing from the online to offline populations. The online population tends to be younger, better educated, and more affluent, which also raises important questions about the potential for reproducing and even amplifying social stratification. Even where the technological access is available, the skills to make use of that access remains

unevenly distributed (DiMaggio et al. 2001; Hargittai 2010; L. Robinson 2011), likely leading to biased levels of participation across kinds of online spaces.

Nevertheless, these differences do not warrant the widely-used distinction between the Web and the “real world,” with the implication that users enter a metaphysical realm every time they open their browser. The online world is not identical to the offline, but it is entirely real. Users who desire status, admiration, social approval, and attention in their offline relationships will bring those desires with them to their online networks. Individuals must navigate many of the same social obstacles online as they do offline as they seek information, political support, friendship, romance, or consumer goods.

While the activities and populations in the online world differ from the offline counterparts, the differences are rapidly declining as Internet access and use of the Web becomes increasingly universal and online interactions becoming more fully integrated with people’s daily offline activities. Today, the majority (63%) of U.S. adults are Internet users, and home Internet access predominantly takes the form of high-speed, broadband connections (Horrigan 2009). Mobile phones are rapidly replacing desktop computers as the online portal, as 45% of U.S. adults in 2013 reported having a smartphone. Paradoxically, global cell phone use is increasing particularly fast in developing countries that lack the infrastructure for landline access.

Due to the network externality of communication media, as the numbers of users increases, online resources have become the primary mechanism by which people engage in many everyday activities, such as following the news, arguing about politics, sports, music, and movies, maintaining social ties with friends and family,

shopping, dating, and even seeking employment. An early study (Wellman and Hampton 1999) found online and offline networks were already merging as early as the 1990s, as neighborhoods and local communities began to use electronic communication tools to augment their existing modes of communication. Today mobile technologies and social media websites like Facebook and Twitter provide a seamless transition between the offline and online worlds (Rainie and Wellman 2012; Xie et al. 2012). While some online communities continue to permit pseudonyms, both Facebook and Google Plus require users to disclose (and verify) their offline identity, supplemented by a detailed profile that includes location, photograph, organizational affiliations, and interests and activities. Even in environments in which users remain pseudonymous, they often establish longstanding and cherished identities and reputations that they are reluctant to cast off.

The mobile Web is particularly important in bridging the online and offline worlds. Survey respondents reported feeling an obligation to have their mobile phone on at all times so as to not miss out on social interaction (Smith 2011, 2012). When Internet access took place primarily at a desk, the temporal patterns of electronic social interaction typically matched the temporal patterns of school and work (Golder et al. 2007; Grinter and Palen 2002). Those temporal and spatial constraints are loosening as Internet access becomes increasingly mobile, allowing users to interact online in the course of their offline activities in real time, independently of time and place.

Representativeness of research participants has long been a concern in lab experiments, especially when the subject pool has consisted largely of college

sophomores (Sears 1986), recently dubbed "WEIRD," an acronym for Western, educated, industrialized, rich and democratic (Henrich et al. 2010). Though some of these sample biases exist in online access as well, online communities in many cases span not only age and class ranges, but also diverse global cultures.

Though online communities may differ fundamentally in the demographic profile of their users, not only from the offline world but even from other online communities, these differences can also open up research possibilities. Just as offline social clubs, community groups, street gangs, firms, and specialized organizations can be opportunities for comparative case studies, so too can highly idiosyncratic online communities like Couchsurfing and a local message board. In sum, online interaction is already deeply woven into the daily experience of millions of people worldwide, and the numbers are rapidly growing. Though differential levels of access, skills, and engagement persist, those differences are declining as usage becomes increasingly universal. For millions, socializing, dating, shopping and learning take place in a digital environment that is second nature.

Methods, Skills, and Training

A primarily obstacle to online research by social scientists is the need for advanced technical training to collect, store, manipulate, analyze, and validate massive quantities of semi-structured data, such as text generated by hundreds of millions of social media users. In addition, advanced programming skills are required to interact with specialized or custom hardware, to execute tasks in parallel on computing grids composed of hundreds of nodes that span the globe, and simply to ensure that very large amounts of data consume memory efficiently and are processed using algorithms

that run in a reasonable amount of time. As a consequence, the first wave of studies of online behavior and interaction has been dominated by physical, computer, and information scientists who may lack the theoretical grounding necessary to know where to look, what questions to ask, or what the results may imply. In the short term, multi-disciplinary collaborations can be highly fruitful, but the long run solution is for graduate programs in the social sciences to adapt to the era of “big data” by providing training in skills that are needed for online research. The list includes:

- Making use of programming interfaces. Many commercial services, in the interest of interoperating with other services as well as third-party software developers, provide application programming interfaces (APIs) that make it possible to download data from the service in a structured and permissible way. In order to use an API, the researcher must typically first register for an "API key" or unique access token, and then write a script to successively query the service and retrieve the desired information.
- Manipulating unstructured data and nested data structures. Data retrieved via APIs is often structured very differently from the flat files that social scientists are trained to work with. Online data are likely to have nested structures, as in XML or JSON documents, that cannot be directly imported into standard statistical packages. Learning to use regular expressions makes it much easier to transform data from human-readable to machine-readable format.
- Creating Web pages and databases to collect and store surveys or online experiments. Online services like Survey Monkey and Amazon Mechanical

Turk make it possible to conduct online surveys and experiments easily and inexpensively, but for studies that require specialized platforms, researchers may need to build a custom website.

- Manipulating and storing large datasets. Finding the degree distribution or average path length in a social network with hundreds of millions of individuals, or the relative frequency of positive and negative emotion words in a large text corpus (Golder and Macy 2011), could be impractical or impossible on a single computer. However, the problem of computational load can be addressed by parallelizing the task on a computer cluster. Among the most important innovations in computing in the past decade has been the development of the MapReduce programming paradigm (Dean and Ghemawat 2004) and the availability of commodity cloud storage. Developed at Google to process the petabytes of Web pages the search engine collects, MapReduce provides a convenient way to process data that is too large to process (or even fit) on a single computer. A series of transformations are performed in succession on subsets of a large dataset, each of which resides on a different computer or processing node. Following these transformations, aggregations are performed so that summary statistics may be generated. Storing large datasets has similarly been made easier, due to the availability of commodity cloud storage. For example, Amazon.com's Web Services and Microsoft's Azure¹¹ platform rent Internet-based computing resources, such as servers that

¹¹ See <http://aws.amazon.com> and <http://windowsazure.com>, respectively.

can be used for pennies per hour, or storage that costs pennies per gigabyte. Researchers faced with spending thousands of dollars of research funds on computer hardware may find this to be a cost-effective alternative, since there is no upfront cost, resources may be turned off when no longer needed, and IT staff do not need to be hired to support to manage the equipment.

- Machine learning and topic modeling. Machine learning refers to statistical techniques that use past observations to classify new observations or make predictions about the associated outcomes. These techniques may be useful when data have nonlinear relationships or a large number of variables that interact in a complex system in ways that cannot be modeled by traditional regression-based methods. Applications range from understanding natural human language to detecting which emails are spam. For example, Support Vector Machines and decision trees make it possible for researchers to code only a random sample from a massive set of observations and approximate the rest. Text analysis techniques like Latent Dirichlet Allocation (LDA) perform unsupervised topic modeling, or automatic clustering of the words found in a body of texts into topical groups (Blei, Ng, and Jordan 2003) by examining the co-occurrences of the words found within. Sentiment analysis uses a combination of statistical techniques and human-created lexicons to identify the valence and intensity of various emotional states expressed in a body of text. Libraries that perform some of these techniques are available in R, or in

standalone software packages like University of Waikato's Weka¹² or Stanford's Topic Modeling Toolbox.¹³

One reason these methods have not gained greater currency in the social sciences is that many current applications are deliberately atheoretical, placing higher value on the ability to predict future observations than on testing a theoretically motivated hypothesis. However, one should not throw out the methodological baby with the atheoretical bath water. After all, every research method, from linear regression to participant observation, can be applied descriptively, with little or no theoretical direction, or analytically, in a program of research that targets the underlying causal mechanisms. Online data opens up transformative possibilities for both descriptive and analytical studies, but without the automated data management and coding tools developed by computer scientists, the analysis of massive unstructured data will remain beyond the reach of most social scientists, leaving the field to disciplines that are much better at building powerful telescopes than at knowing where to point them (Lazer et al. 2009; Watts 2012). Although few social science departments are currently able to incorporate these skills into graduate methods courses, interested students can be directed to computer and information science departments for specialized training.

Conclusion

In the earliest days of the field of information theory, Claude Shannon's (1956) Bandwagon essay warned that the flurry of interest in the new field would generate a

¹² <http://www.cs.waikato.ac.nz/ml/weka/>

large amount of low-quality work, but this should not lead the research community to conclude that this was an inherent limitation. On the contrary, it should be taken as an exhortation to focus on producing more rigorous studies. Shannon's advice may apply as well to the coming era of online social science. The unprecedented opportunity to observe human behavior and social interaction in real time, at a microscopic level yet on a global scale, is attracting widespread interest among scientists with the requisite skills to mine these data but not always with the theoretical background needed to guide the inquiry. Studies that identify patterns of behavior or map social landscapes invite dismissal as "atheoretic empiricism," but this may be shortsighted. These pioneering studies should instead be taken as evidence not of the most that can be learned from online research but of the vast opportunities that lie ahead for a new science of social life.

¹³ <http://nlp.stanford.edu/software/tmt/tmt-0.4/>

CHAPTER 2
DIURNAL AND SEASONAL MOOD TRACKS WORK,
SLEEP AND DAYLENGTH ACROSS DIVERSE CULTURES¹⁴

Individual mood is an affective state that is important for physical and emotional well-being, working memory, creativity, decision-making (Ashby, Valentin, and Turken 2002), and immune response (Seegerstrom and Sephton 2010). Mood is influenced by levels of dopamine, serotonin and other neurochemicals (Ashby et al. 2002), as well as hormonal levels (e.g. cortisol) (Kirschbaum and Hellhammer 1989). Mood is also externally modified by social activity, such as daily routines of work, commuting, and eating (Stone et al. 2006; Vittengl and Holt 1998). Because of this complexity, accurate measurement of affective rhythms at the individual level has proven elusive.

Experimental psychologists have repeatedly demonstrated that positive and negative affect are independent dimensions. Positive affect (PA) includes enthusiasm, delight, activeness and alertness, while negative affect (NA) includes distress, fear, anger, guilt and disgust (Clark, Watson, and Leeka 1989). Thus, low PA indicates the absence of positive feelings, not the presence of negative.

Laboratory studies have shown that diurnal mood swings reflect endogenous

¹⁴ A version of this chapter was published as Golder, S. and Macy, M. (2011) “Diurnal and Seasonal Mood Vary with Work, Sleep and Daylength Across Diverse Cultures.” *Science*. 333:1878–81. The data used in this chapter was collected in collaboration with Vladimir Barash, who I thank for his assistance. This research was supported by the National Science Foundation (BCS-0537606, IIS-0705774, and IIS-0910664) and was conducted using the resources of the Cornell University Center for

circadian rhythms interacting with the duration of prior wakefulness or sleep. The circadian component corresponds to changes in core body temperature which is lowest at the end of the night and peaks during late afternoon. The sleep-dependent component is elevated at waking and declines throughout the day (Boivin et al. 1997). Other studies have variously observed a single PA peak 8-10 hours after waking (Hasler et al. 2008), a plateau from noon to 9:00 pm (Clark et al. 1989), and two daily peaks at noon and evening (Stone et al. 2006) or afternoon and evening (Vittengl and Holt 1998). Some PA studies have also reported a "siesta effect" or mid-afternoon dip (Clark et al. 1989). Results for NA have also been inconclusive, with peaks observed in the midmorning (Stone et al. 2006) as well as the afternoon (Stone et al. 2006; Vittengl and Holt 1998) and evening (Vittengl and Holt 1998). Several studies have also found that NA is not subject to diurnal variation (Clark et al. 1989; Hasler et al. 2008).

Although these studies have improved our understanding of affective rhythms, they have relied heavily on small homogeneous samples of American undergraduates (Clark et al. 1989; Hasler et al. 2008; Vittengl and Holt 1998) who are not necessarily representative of the larger population (Henrich et al. 2010). Students are exposed to varying academic schedules that constrain when and how much they sleep. Further, these studies typically rely on retrospective self-reports, a method that limits temporal granularity and is vulnerable to memory error and experimenter demand effects. Researchers have acknowledged the limitations of this methodology (Bolger, Davis,

and Rafaeli 2003) but they had no practical means for in-situ real time hourly observation of individual behavior in large and culturally diverse populations over many weeks.

That is now changing. Data from increasingly popular online social media allow social scientists to study individual behavior in real time in a way that is both fine-grained and massively global in scale (Lazer et al. 2009), making it possible to obtain precise real-time measurements across large and diverse populations.

Several recent studies have examined the affective and semantic content of messages from online sources like Twitter, a micro-blogging site that records short time-stamped public comments from hundreds of millions of people worldwide (Bollen, Pepe, and Mao 2010; Dodds and Danforth 2010; Kramer 2010; O'Connor et al. 2010). Using data from Twitter, O'Connor et al. (2010) found that opinion about specific issues and political candidates varied from day to day. Dodds and Danforth (2010) showed how the affective valence of songs, musicians and blog posts depend on the day of week, especially holidays. In an unpublished study, Mislove et al. (n.d.) used Twitter messages to examine what they refer to as the "pulse of the nation" as it varies across the week and moves across time zones. These studies, by computer and information scientists, conflate diurnal changes within each individual with baseline differences in affect across individuals of different chronotypes (sleep-wake cycles), who tend to be active at different times of the day. If "morning people" and "night owls" differ in baseline affect, this will confound within-individual changes in affect from morning to night. These studies also collapsed positive and negative affect into a single dimension, contrary to previous research that has consistently shown these to be

largely independent dimensions. As a consequence, the reported patterns cannot be unambiguously interpreted.

This study also uses data from Twitter. The 140-character limit on message length allows conversation-like exchanges. Text analysis of these messages provides a detailed measure of individuals' spontaneous affective expressions across the globe. PA and NA are measured using a prominent lexicon for text analysis, Linguistic Inquiry and Word Count (Pennebaker et al. 2001). The LIWC lexicon was designed to analyze diverse genres of text, such as “emails, speeches, poems, or transcribed daily speech.” LIWC contains lists of words or word stems that measure 64 behavioral and psychological dimensions including PA and NA as well as "anxiousness," "anger" and "inhibition." These lists were created using emotion rating scales and thesauruses and validated by independent judges. Bantum & Owen (2009) found that LIWC's sensitivity and specificity for all emotional expression words were .88 and .97 respectively. I used a lexicon containing only English words, and all reported results include only English speakers; the English proficiency measure is described below and its distribution is shown in Figure 1.

I analyzed changes in hourly, daily and seasonal affect at the individual level in 84 countries (see Table 1). In contrast to the self-report methodology used in off-line studies, these measures were not prompted by an experimenter nor recollected after the fact. Rather, they were obtained in real time, directly from comments composed by the individuals and are therefore less vulnerable to memory bias and experimenter demand effects. Most importantly, instead of relying on a small sample of American undergraduates, I measured affective changes among millions of Twitter

users worldwide, allowing cross-societal tests of cultural and geographic influences on affective patterns.

Using Twitter.com's data-access protocol, I collected up to 400 public messages from each user in the sample, excluding users with fewer than 25 messages. The resulting corpus contained approximately 2.4M individuals from across the globe and 509M messages authored between February 2008 and January 2010.

I removed between-individual differences by mean-centering the measures of PA and NA at the individual level. Figure 1 shows the within-individual PA/NA by hour and day for English-speaking individuals worldwide, in local time, including 95% confidence intervals (Between individual effects are shown in Figure 2). The shapes of the affective rhythms were nearly identical across days of the week for both PA and NA. PA peaks twice: relatively early in the morning and again near midnight.

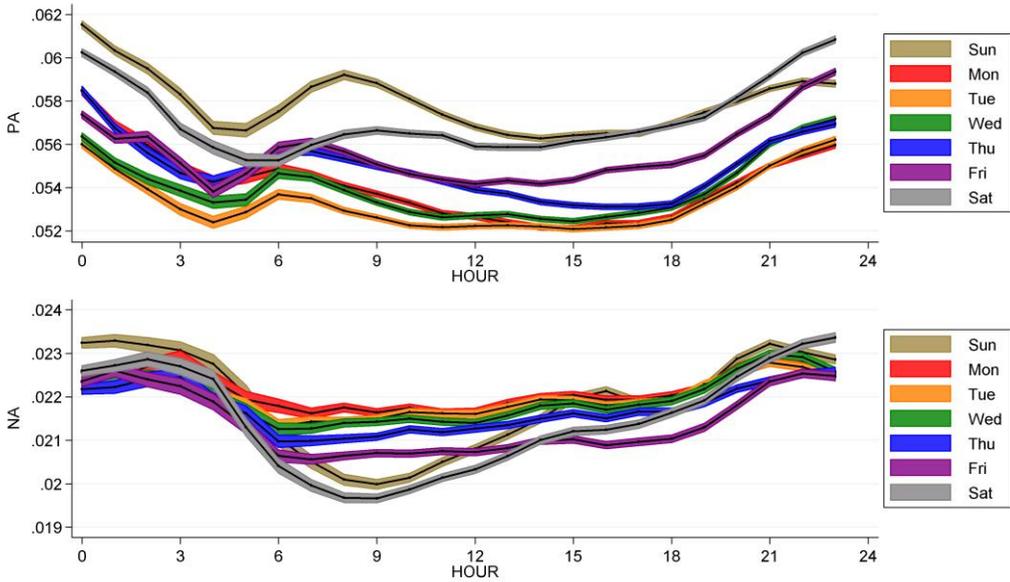


Figure 1. Hourly changes in individual affect broken down by day of the week. Each series shows mean affect (black lines) and 95% confidence interval (colored regions).

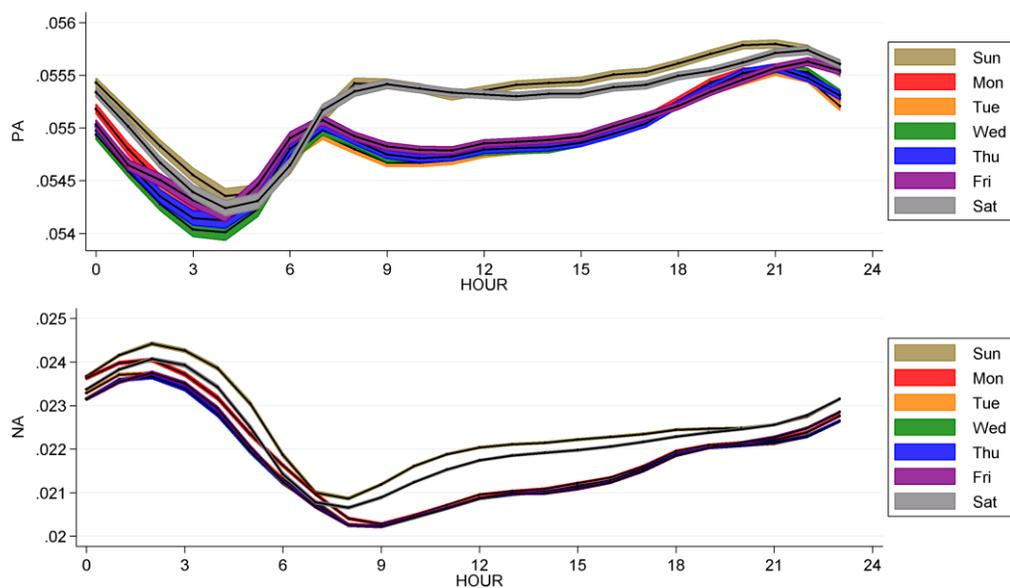


Figure 2. Hourly changes in between-individual affect (y-axis) over a 24-hour cycle (x-axis), broken down by day of the week. Each series shows the mean affect (black lines) and 95% confidence interval (colored regions).

Although the shape of the rhythm was consistent across days, PA levels were generally higher on Saturday and Sunday ($M=0.058$) than at any time during the weekdays ($M=0.054$, $p \approx 0.00$), which points to possible effects of work-related stress, less sleep, and earlier wake time. PA decreased midmorning as the work day begins, and increased in the evening as the work day ends. However, the fact that the shape of the affective cycle was similar on both weekends and weekdays points to sleep and the biological clock as important determinants of affect, regardless of the variations in environmental stress. Moreover, the morning (3:00 am to noon) peak on Saturday and Sunday was delayed by nearly two hours ($M=9:48\text{am}$ vs. $M=7:55\text{am}$, $p \approx 0.00$), the amount of time people might be expected to "sleep in," allowing themselves to be awakened not by the alarm clock, but by the body clock.

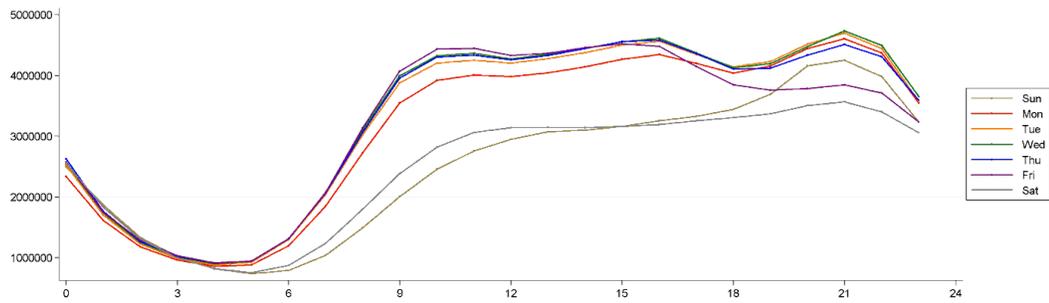


Figure 3. Number of messages posted on Twitter (y-axis) by hour (x-axis) and day of the week.

NA was lowest in the morning and rose throughout the day to a nighttime peak, a pattern that also suggests that people may be emotionally "refreshed" by sleep. Compared to PA, NA varies less intraday, except the morning trough deepens as the work week progresses, rebounding on Sunday. It is only between midnight and 6:00 am that NA was the mirror image of PA, with NA declining and PA increasing. For the rest of the day, PA and NA moved in parallel, reflected in the small correlation ($r=-0.08$).

These patterns varied for individuals of different chronotypes. Most people are most active in the afternoon and evening and message volume is highest between 9:00am and 10:00pm (see Figure 3). However, "Night owls," or people most active late at night, exhibit markedly different rhythms in both PA and NA (Figure 4).

Despite these differences between chronotypes, the temporal affective pattern is similarly-shaped across disparate cultures and geographic locations. Figure 5 shows diurnal rhythms (based on local time) for four groups of countries: US and Canada; UK, Australia, Ireland and New Zealand; India; and English-speaking Africa. Although the rhythms across these regions are not statistically indistinguishable ($X^2(69, N=226.7M) = 852556, p \approx 0.00$), the patterns mirror those observed in Figure 1:

a morning rise and night-time peak in PA and a sharp drop in NA during the overnight hours.

This similarity is consistent with a biological explanation based on the correspondence between the circadian clock and sleep (Daan, Beersma, and Borbely 1984), but sleep patterns in turn partially depend on the organization of the work day and work week. For most of the developed world, people typically work Monday to Friday from nine to five. However, in the United Arab Emirates the traditional work week runs Sunday-Thursday (Portal 2010). This allows for a natural experiment. If diurnal rhythms are affected by sleep schedules that are shaped by cultural norms, we would expect Friday and Saturday in the UAE to have higher baseline PA and a later morning peak than during the rest of the week. This is confirmed by the intraday

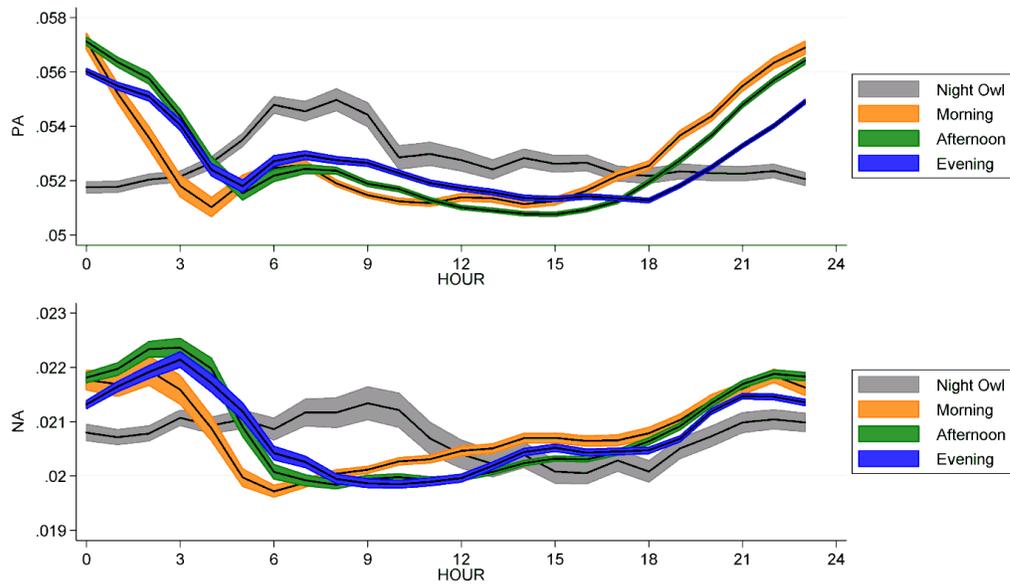


Figure 4. Hourly changes in within-individual affect (y-axis) over a 24-hour cycle (x-axis), broken down by chronotype, for PA (top) and NA (bottom). Each series shows the mean affect (black lines) and 95% confidence interval (colored regions).

pattern in the UAE, which mirrors the global pattern with higher PA on the weekend (Friday and Saturday; $M=0.057$) than during the work week (Sunday to Thursday; $M=0.055$, $p \approx 0.00$), and a delayed PA peak on Friday and Saturday of nearly two hours ($M=9:53\text{am}$ vs. $8:04\text{am}$, $p \approx 0.00$). Though the workday in the UAE begins earlier than it does in the west (Portal 2010), the UAE does not differ in the timing of its morning PA peak.

The importance of sleep and the biological clock for affective rhythms may extend beyond diurnal rhythms to seasonal patterns as well. However, like diurnal mood studies, previous research on seasonal mood changes has relied on small samples within single countries and is severely constrained by the difficulty collecting data over an entire year (Lam and Levitan 2000). Clinical research has found higher prevalence of depressive anxiety in winter the further north the latitude (Rosenthal et

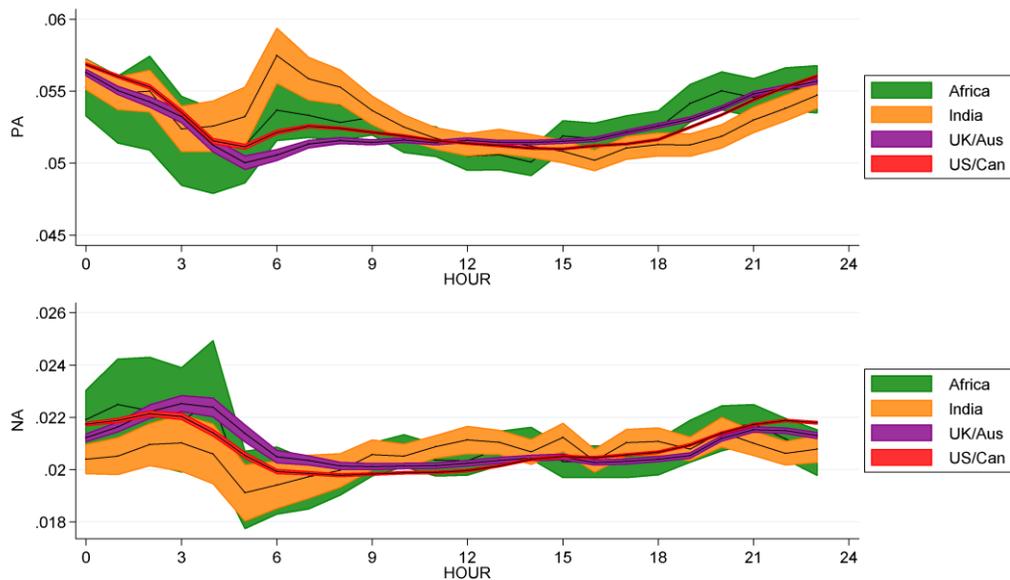


Figure 5. Hourly changes in individual affect in four English-speaking regions. Each series shows mean affect (black lines) and 95% confidence interval (colored regions).

al. 1984). Although originally attributed to insufficient exposure to light (Rosenthal et al. 1984), more recent research on seasonal mood variation supports the “phase-shift hypothesis,” which points to the importance of the timing of the dawn signal to synchronize the circadian pacemaker (Terman and Terman 2005).

I therefore examined how PA and NA vary within individuals with seasonal changes in daylength. The length of the day at a given location varies sinusoidally over the year, with higher amplitude waves the farther one moves from the equator, resulting in long summer days and short winter days in extreme latitudes, and consistent daylength equatorially. Daylength is modeled using two parameters, latitude and day of the year (Forsythe et al. 1995). I then measured the relative change in daylength using the slope of the line tangent to the daylength curve, which indicates whether the Summer solstice (positive slope) or Winter solstice (negative slope) is

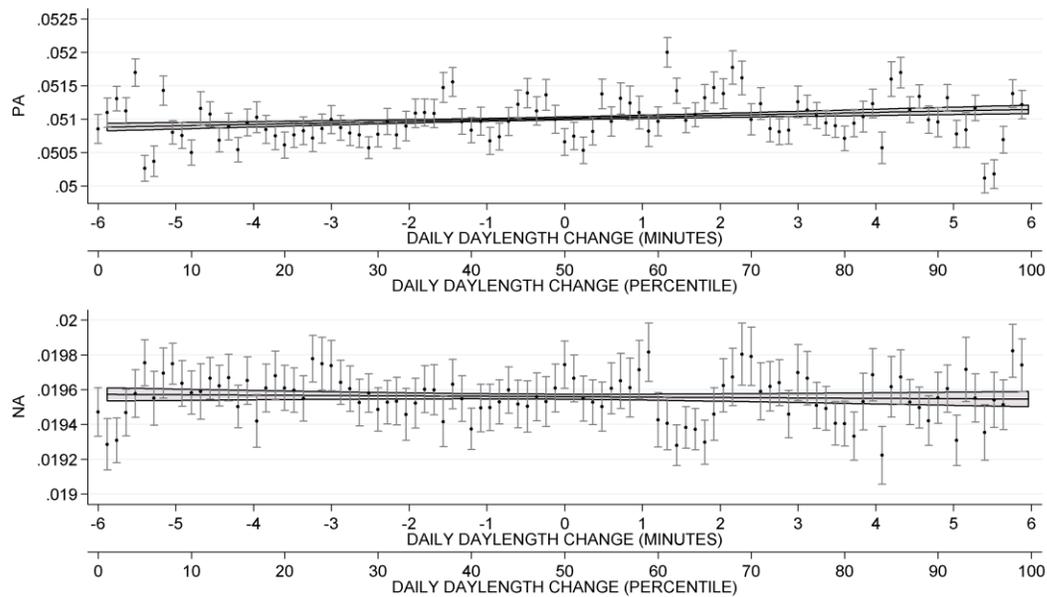


Figure 6. Line of best fit through the 14.3M person-month observations (affect by minutes gained or lost per day). For visual reference, 100 aggregate observations binned by percentiles are superimposed.

approaching. I also measured absolute daylength as the interval between sunrise and sunset.

I found no effect of absolute daylength on either PA ($r=3.14 \times 10^{-5}$, $p=0.905$) or NA ($r=-5.14 \times 10^{-4}$, $p=0.052$). However, as predicted by the phase-shift hypothesis, I observed a change in affect with relative daylength. Figure 6 shows the best-fitting line through 14.3M observations (affect by minutes gained or lost per day), as well as the 95% confidence interval. (For visual reference, I also superimposed 100 aggregate observations binned by percentiles.) The positive slope in the upper panel of Figure 6 shows how baseline PA (averaged over each person-month) increases when daylength is increasing (as the summer solstice approaches), but decreases as the winter approaches ($r=1.21 \times 10^{-3}$, $p \approx 0.00$). In contrast, NA does not change ($r=1.86 \times 10^{-4}$, $p=0.483$). This result supports findings using survey methods that show seasonal changes in PA but not NA (Murray, Allen, and Trinder 2001), and suggests that "winter blues" (Rosenthal 2006) is associated with diminished positive affect but not increased negative. The increased baseline PA approaching the summer solstice may correspond to the earlier dawn signal, thereby reducing the discrepancy between social and biological timing.

Although the analysis of online messages makes it possible to track changes in affect in ways that are not feasible offline, there are also important limitations. First, unlike laboratory studies, I have little data on demographic or occupational backgrounds that may influence when and how much people sleep, the level and timing of environmental stress, susceptibility to affective contagion, and access to social support -- conditions that are known to influence mood. Second, lexical analysis

measures the expression of affect, not the experience. Cultural norms may regulate the appropriateness of affective expression at different times of the day or week. Since these norms are unlikely to be universal, the robust patterns I observed across diverse cultures (as well as across days of the week) gives us confidence that affective expression is a reliable indicator of diurnal individual-level variations in affective state.

Data Description

During the month of January 2010, I sampled all Twitter user accounts created between February 2008 and April 2009, collecting up to 400 messages from each account. Therefore, the messages in our sample were all written in the time period beginning in February 2008 and ending in January 2010. I do not expect that the results would have differed by sampling a different time period. The measures of PA and NA are, in general, normally distributed. Since person-hour PA and NA are fractions of words (lexicon words divided by total words), their values range from 0 to 1, that is, from no PA/NA words to only PA/NA words. Person-hours would not be expected to be normally distributed, and indeed they are not ($N=139.6M$; $M=0.0551$, $SD=0.0748$ and $M=0.0218$, $SD=0.0490$ for PA and NA, respectively). However, users' baseline PA (averaged over $24*7=168$ time points for each user) is normally distributed ($N=2.06M$; $M=0.0552$, $SD=0.0214$), as is NA ($M=0.0212$, $SD=0.0140$). The individual mean PA and NA for entire countries ($N=84$) are also normally distributed ($M=0.0534$, $SD=0.0031$) and ($M=0.0199$, $SD=0.0021$), and no countries have extreme values.

Though large and diverse, the data is not statistically representative of the

global population or that of any particular country. In particular, we do not know the gender, race or age distributions of our sample, nor of the socioeconomic or occupational attributes of the individuals in the dataset. Because interest in and access to the internet are characterized by deep "digital divides" (DiMaggio et al. 2001) that separate people by demographic and socio-economic differences, we would not expect the sample to represent demographic categories in proportion to their numbers in the population. A recent survey by Arbitron and Edison Research (Webster 2010) reports that Twitter users are 51% white, 24% African American and 17% Hispanic, and people with college and advanced degrees are overrepresented, as are people with higher household incomes. Therefore, this sample includes far more diverse demographic categories than an earlier generation of laboratory-based studies of diurnal affective rhythms, which have been limited almost entirely to U.S. undergraduates.

Time & Location

Each message received using the Twitter API is time-stamped relative to UTC (Coordinated Universal Time). However, most Twitter users' accounts include their self-reported time zones (e.g. "(GMT -05:00) Eastern Time (US & Canada)", "(GMT -06:00) Mexico City", "(GMT +01:00) Rome") which identify not only a distance from UTC, but also the user's country of residence. Using this information, I used the Java Calendar and TimeZone classes to normalize all time-stamps to local time, as well as identify daylight savings time in that location. I used the 141 time zone codes to identify individuals by country and, in some cases, city. Table 1 shows the mapping of time zones to countries.

Table 1. Time zones and countries/regions.

Country/Region	Country Group	English Proficiency ≥ 0.8	Time Zone	Notes
Afghanistan		91%	Kabul	(excluded) ^(a)
Argentina		22%	Buenos Aires	
Armenia		55%	Yerevan	
Australia	3	97%	Adelaide Brisbane Canberra Darwin Hobart Melbourne Perth Sydney	
Austria		31%	Vienna	
Azerbaijan		30%	Baku	
Azores		29%	Azores	
Bangladesh		82%	Dhaka	
Belarus		26%	Minsk	
Belgium		46%	Brussels	
Bolivia		33%	La Paz	
Bosnia and Herzegovina		48%	Sarajevo	
Brazil		2%	Brasilia	
Bulgaria		65%	Sofia	
Burma		85%	Rangoon	
Canada	1	92%	Atlantic Time (Canada) Newfoundland Saskatchewan	
Cape Verde		61%	Cape Verde Is.	
Central America		51%	Central America	San Salvador
Chile		14%	Santiago	
China		56%	Beijing Chongqing Hong Kong Urumqi	
Colombia		31%	Bogota	
Croatia		37%	Zagreb	
Czech Republic		25%	Prague	
Denmark		45%	Copenhagen	

Ecuador		94%	Quito	(excluded) ^(c)
Egypt		79%	Cairo	
Estonia		40%	Tallinn	
Fiji		68%	Fiji	
Finland		65%	Helsinki	
France		30%	Paris	
Georgia		48%	Tbilisi	
Germany		20%	Berlin	
Greece		57%	Athens	
Greenland			Greenland	(excluded) ^(d)
Hungary		26%	Budapest	
India	2	91%	Chennai Kolkata Mumbai New Delhi	
Indonesia		16%	Jakarta	
Iran		84%	Tehran	(excluded) ^(b)
Iraq		84%	Baghdad	(excluded) ^(a)
Ireland	3	95%	Dublin	
Israel		80%	Jerusalem	
Italy		31%	Rome	
Japan		12%	Osaka Sapporo Tokyo	
Kazakhstan		35%	Almaty Astana	
Kenya	4	90%	Nairobi	
Korea		38%	Seoul	
Kuwait		83%	Kuwait	
Latvia		18%	Riga	
Liberia	4	70%	Monrovia	
Lithuania		25%	Vilnius	
Macedonia		52%	Skopje	
Malaysia		74%	Kuala Lumpur	
Marshall Islands		57%	Marshall Is.	
Mexico		20%	Chihuahua Guadalajara Mazatlan Mexico City Monterrey	

			Tijuana
Mongolia		51%	Ulaan Bataar
Morocco		54%	Casablanca
NA			Georgetown (excluded) ^(d)
			International Date Line West (excluded) ^(d)
			Mid-Atlantic (excluded) ^(d)
			Midway Island (excluded) ^(d)
			New Caledonia (excluded) ^(d)
			West Central Africa (excluded) ^(d)
Nepal		79%	Kathmandu
Netherlands		26%	Amsterdam
New Zealand	3	96%	Auckland
			Wellington
Oman		80%	Muscat
Pakistan		81%	Islamabad
			Karachi
Papua New Guinea		88%	Port Moresby
Peru		35%	Lima
Poland		53%	Warsaw
Portugal		20%	Lisbon
Romania		25%	Bucharest
Russia		26%	Ekaterinburg
			Irkutsk
			Kamchatka
			Krasnoyarsk
			Kyiv
			Magadan
			Moscow
			Novosibirsk
			St. Petersburg
			Vladivostok
			Volgograd
			Yakutsk
Samoa		71%	Samoa
Saudi Arabia		76%	Riyadh
Serbia		39%	Belgrade
Singapore		91%	Singapore
Slovakia		37%	Bratislava
Slovenia		41%	Ljubljana
Solomon Islands		42%	Solomon Is.

South Africa	4	95%	Pretoria Harare
Spain		18%	Madrid
Sri Lanka		85%	Sri Jayawardenepura
Sweden		33%	Stockholm
Switzerland		39%	Bern
Taiwan		36%	Taipei
Thailand		47%	Bangkok
Tonga		68%	Nuku'alofa
Turkey		20%	Istanbul
UK	3	97%	Edinburgh London
United Arab Emirates		87%	Abu Dhabi
USA	1	95%	Alaska Arizona Central Time (US & Canada) Chicago Eastern Time (US & Canada) New York City Guam (excluded) ^(d) Hawaii Indiana (East) Mountain Time (US & Canada) Phoenix, AZ Pacific Time (US & Canada) Los Angeles
Uzbekistan		48%	Tashkent
Venezuela		19%	Caracas
Vietnam		39%	Hanoi

^(a) Afghanistan and Iraq are excluded due to the counfound with Americans located there.

^(b) Iran is excluded due to the prevalence of Western activists who changed their time zones to Tehran as a gesture of political support.

^(c) Ecuador is excluded because a relatively large number of users are identified with this time zone who do not, in fact, appear to be connected to Ecuador.

^(d) Some other time zones are excluded because they cannot be identified geo-spatially, have no users, or are associated with small islands whose internet-connected inhabitants are likely to be mainly from other places.

Lexicons and Affect Measurement

I measured time in two ways, as hour of the day (0-23) to capture diurnal variation, and as hour of the week (0-167) to capture inter-day variation in diurnal cycles (with Sunday designated as 0-23, Monday as 24-47, and so on). I measured mean affect during each person-hour, giving either 24 or 168 observations for each

individual, depending on whether the 24-hour time scale is disaggregated by day of the week. For each hour, I counted the number of words across all messages by an individual that appeared in the positive and negative word lists, respectively. I then expressed that number as a proportion of all words in all messages by an individual in that person-hour (including words that did not appear in the lexicon). Formally,

$$PA_u(h) = \frac{\|PAWORDS_u(h)\|}{\|WORDS_u(h)\|} \quad (1)$$

where $h \in H$ and $H = \{0 \dots 167\}$, or the 168 hours of the week (24 hours/day * 7 days). The measure for NA was computed similarly, as were the measures taken over 24 hours.

Person-hours were weighted equally regardless of the number of messages within them, based on our interest in measuring the affect of the individuals in the Twitter population, not the Twitter corpus itself. Thus, verbose and laconic individuals contribute equally to the mean. (I tested for possible correlation between verbosity and affect and found none.) Finally, the measures of affect are based on proportions rather than raw counts of word occurrences and are therefore not biased by variation in Twitter activity from hour to hour or day to day; this variation is shown in Figure 3.

Measures of positive and negative affect

Intuitively, positive (PA) and negative affect (NA) might seem to designate opposite ends of a single affective spectrum. However, almost all laboratory studies of diurnal rhythms have used separate measures of PA and NA, based on consistent empirical evidence that the two measures vary independently (Clark et al. 1989; Hasler et al. 2008; Stone et al. 2006; Vittengl and Holt 1998). Positive affect

comprises feelings such as enthusiasm, delight, activeness and alertness, while negative affect comprises feelings like distress, fear, anger, guilt and disgust (Clark et al. 1989). Thus, low positive affect indicates the absence of positive feelings, not the presence of negative. For example, psychologists point out that suicide is typically associated with high negative affect and is most common in mid-morning, when alertness – a component of positive affect – is highest (Stone et al. 2006). These results confirm what an earlier generation of researchers have found using self-reports – PA and NA are insufficiently correlated to warrant collapse into a unidimensional measure. As noted earlier, I measured the correlation between the within-individual PA and NA scores for each person-hour in our data. A strong negative correlation would support the use of a unidimensional measure, while a correlation close to zero would indicate the need for separate measures. The observed correlation ($r=-0.08$) is close to zero, reflecting the underlying independence of PA and NA.

Measures of within-individual and between-individual variation.

Previous laboratory research on affective change has focused on diurnal variation within the individual, not on changes in the collective mood of an entire population. The two measures are not equivalent since changes in the collective mood could be due to affective differences between individuals whose activity is concentrated at different times of the day. In contrast to psychologists, who have focused on variation within the individual, recent studies by computer and information scientists (e.g. Mislove et al. (n.d.)), have measured temporal variation in the collective mood, by taking the mean affect across all individuals at each hour. However, this makes it impossible to know whether the reported changes reflect the

aggregation of individual diurnal rhythms or the tendency for individuals who are active at different times of the day (e.g. "morning people" and "night owls") to differ in a mood level that is relatively invariant over time.

Therefore, in order to measure how individuals (rather than the population) vary over time, I decomposed the affect measures into two components: between-individual variation (within hours) and within-individual variation (across hours).

Between-individual variation captures how individuals differ from one another in their baseline affect regardless of the time of day or day of week. It is simply the individual's mean affect across all hours:

$$BPA_u = \overline{PA_u} = \frac{1}{\|H\|} \sum_{h \in H} PA_u(h) \quad (2)$$

Note that the between component is the individual user's mean over time and therefore does not vary from hour to hour.

The within-individual PA score for a person-hour measures the signed difference between the person's score that hour and their baseline as defined in (2). Within-individual scores are comparable across people because individuals' baseline tendencies toward being upbeat or downbeat have been removed, leaving only the change over time that is within each individual:

$$WPA_u(h) = PA_u(h) - BPA_u + \frac{1}{\|UH\|} \sum_{(u,h) \in UH} PA_u(h) \quad (3)$$

where (u, h) pairs indicate user-hours and UH is the set of all such pairs in the

dataset.¹⁵

The final term in (3) is the grand mean across all user-hours; it is a constant and, as noted earlier, is 0.0551 for PA and 0.0218 for NA. It does not change the result beyond shifting the y-axis to aid interpretation.

The following lines of Stata code further explicate the construction of the between- and within-individual measures in the above equations (each row in the dataset is a user-hour):

Stata command	Equation
<code>replace pa = pa / tokens</code>	(1)
<code>by uid, sort: egen pa_b = mean(pa)</code>	(2)
<code>egen pa_gm = mean(pa)</code>	n/a
<code>gen pa_w = pa - pa_b + pa_gm</code>	(3)

Figure 1 plots the mean over all users of within-individual affect for each of 168 hourly observations per user:

$$WPA(h) = \frac{1}{\|U(h)\|} \sum_{u \in U(h)} WPA_u(h) \quad (4)$$

where $U(h)$ is the subset of users who were active during hour h .

Likewise, Figure 2 reports variation over the day and week in mean between-individual PA:

$$BPA(h) = \frac{1}{\|U(h)\|} \sum_{u \in U(h)} BPA_u \quad (5)$$

¹⁵ Throughout this section, I use u to index the set of users but h as an argument to a function. This is because users are discrete entities but time is in principle continuous (even though I measure time as 24 or 168 discrete hours in practice). In other words, I think of PA and NA as continuous functions of time, but for the purposes of measurement, discrete hours are the most convenient units of analysis.

Though BPA_u does not vary over time, the hourly average of the user averages does vary over time, due to changes in the composition of the set of active users, $U(h)$, who differ from one another in their baseline affect. Individuals with different baseline affect levels differ in the time of day when they tend to be active.

Comparison with Figure 1 reveals important differences between individuals' time of peak activity. A similar morning PA peak to the one in Figure 1 indicates that, in addition to individuals experiencing relatively high PA in the morning, it is those individuals with high baseline PA who are most active at this time. On the weekend, there is a similar two-hour delay in peak PA, which plausibly reflects the tendency for activity level to be delayed while "sleeping in." From the morning peak onwards, between-individual PA remains much higher on weekends than on weekdays, suggesting that those individuals most active on the weekend also exhibit the highest baseline PA.

The need to separate between-individual and within-individual affective differences is further supported by evidence of interactions between the two measures. I tested for interaction by comparing within-individual diurnal rhythms across four groups: "morning people," "afternoon people," "evening people," and "night owls," based on when most of their messages were posted on Twitter (6:00 am-12:00 pm, 12:00 pm-6:00 pm, 6:00 pm-12:00 am and 12:00 am-6:00 am).¹⁶ Figure 4 shows that the first three groups are very similar to one another and to the overall pattern of

¹⁶ Users are distributed as follows: late-night ("night owl") 7.41%; morning people 16.46%; afternoon 36.27%; evening 39.86%. The distribution of messages is similar, indicating that no single group dominates the aggregate results.

within-individual changes in both PA and NA reported in Figure 1. High PA levels in the morning followed by a decrease, then increasing again toward the end of the day, and NA levels which peak late at night and are lowest in the morning. However, a very different diurnal pattern is exhibited by "night owls." The morning peak in PA occurs about two hours after the morning peak for everyone else (perhaps because they are sleeping in), and there is no late-night peak. Meanwhile, NA peaks twice for "night owls," but only once for everyone else, and the morning peak occurs when NA is lowest for the other three groups. Though high-NA people tended to be more active late at night, those who are most active at night ("night owls") exhibit neither higher NA at night, nor overall.

Though activity cycles are measured based on the time periods in which users posted the largest number of messages, I do not assume that these users are more active offline during these same times. I discuss these groupings here only in order to demonstrate that temporal variation in affect at the population level cannot be unambiguously attributed to the diurnal rhythms of individuals, due to the confounding effects of affective differences between individuals whose activity on Twitter is concentrated at different times.

Seasonal Variation

My seasonal analysis parallels the diurnal analysis; instead of grouping messages into person-hours, I group messages into person-months. This results in up to 25 months (February 2008 - January 2010) per person in our sample. As with the diurnal analysis, I am interested in within-individual variation, not between-individual changes in aggregate behavior caused by changes in the composition of the population

during a period of very rapid growth in Twitter's user base. Therefore, as for the diurnal analysis, I mean-centered individual affect scores. Mean-centering removes differences between individuals in their baseline affect level while preserving temporal differences (diurnal or seasonal, depending on the time frame of the analysis). Otherwise, the seasonal analysis would be confounded by the tendency for newer cohorts to express greater affect. The explanation for greater affective expression among newer users is outside the scope of our study, but Twitter's rapid growth during these two years may have attracted more mainstream, less technically-oriented users.

Even after mean-centering on person-months, I observed a within-individual increase in affective expression over the two-year period, for both early-adopters as well as successive cohorts. This increase is roughly comparable in magnitude to the amount of diurnal change observed between the peaks and valleys of an individual over the course of a day. This within-individual increase parallels, and perhaps reflects, the between-individual increase associated with an influx of new users, which may have changed expectations about appropriate content among earlier users as well. Whatever the reason for the within-individual increase, it also must be removed in order to isolate hypothesized effects of seasonal changes in daylength. Therefore, after mean-centering individual scores by person-month to remove between-individual differences, I then mean-centered the corrected scores by month for each of the 25 months over the two-year period in the analysis.

The daylength at a given location on a given day is governed by the day of the year and the latitude at that location (Forsythe et al. 1995). Since I know only

individuals' home country and time zone and not their specific location within that country, I cannot pinpoint their precise latitude. As a best approximation, each individual was assigned the latitude of the city associated with their reported time zone. Outside the U.S., time zones are designated by principal cities, as listed in Table 1. For the U.S., I used the latitude of the largest city within each time zone. (As a robustness check, I also assigned these individuals the latitude of the population centroid of their time zone, with no detectable change in the results.) Knowing each individual's approximate latitude, I used the formula provided by Forsythe et al. (1995) to assign each message the number of hours of daylight for that day at that location.

Robustness of Text Analysis

Measurement error and the methodological limitations of automated text analysis have been discussed at length in the technical literature on computational measurement of affect. One way in which automated text analysis might provide spurious results is if a few terms dominate, especially at particular times. For example, morning and evening peaks in PA might be artifacts of frequent occurrences of the word "good," through the use of such phrases as "good morning" and "good night." Fortunately, these expressions do not occur often enough on Twitter to affect the results. Although "good" is the most frequent affective expression on Twitter, and although many of the morning occurrences of "good" are as modifiers of "morning," the expression "good morning" turns out to contribute little to the overall measure of positive affect. This was verified by filtering out expressions that might distort the affect measures. When analyses were repeated excluding all instances of "good"

followed by “morning” and “night,” the results showed no discernible differences.

A potentially more troublesome scenario is the occurrence of “good” preceded by “not,” which has the opposite affective implication. In this corpus, “good” appears, at maximum, in 4.93% of messages in a given hour, while “not good” appears at maximum in 0.049% of messages per hour, a difference of two orders of magnitude. This difference implies that the potential for “not good” to distort the results for “good” is quite minimal. Similarly, the proportions for “happy” and “not happy” are 2.37% and 0.027%, respectively. As with "good morning" and "good night," filtering out all occurrences of terms in the PA and NA lexicons that are preceded by "not" had no discernible effects.

The internet has given rise to a variety of affective indicators that are specific to the genre of internet conversations. The most prominent of these are "emoticons," or facial expressions represented typographically, such as the "smiley face," represented with or without a nose as :-) and :) as well as its frowning counterpart, represented as :-(and :(.

Unlike the LIWC lexicon, emoticons have not been used to track affective changes, and there are no studies confirming the validity of emotions as a measure of affective expressions. Nevertheless, I examined temporal changes in the use of smiling and frowning emoticons and found that usage was too sparse to be able to detect a consistent pattern. To get around the problem of sparse data, I combined the emoticons with the LIWC PA and NA lists, in effect treating each emoticon as a "word" in the lexicon. However, including the emoticons had no visible effect on the patterns reported in Figure 1.

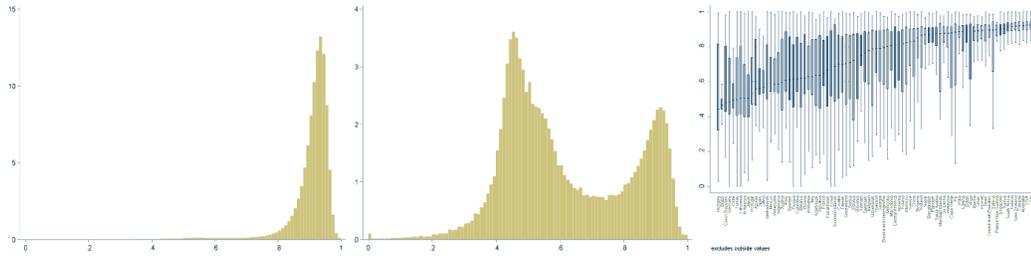


Figure 7. English proficiency across the population. Left: Histogram of individual English proficiency in English-speaking countries shown in Figure 5. Middle: Histogram of individual English proficiency in all other countries. Right: Boxplots of English proficiency in each country/region.

Cross-Cultural Analysis and English Proficiency

The cross-cultural analysis in Figure 5 is limited to countries in which English is a primary language, but in some cases other languages are also in widespread use. Moreover, English is not the primary language in many of the larger set of 84 countries included in the seasonal analyses. Therefore, in addition to limiting our analysis to speakers of English, I tested whether our lexical measures for PA and NA are sensitive to English proficiency and dialect. To that end, I assigned each individual a proficiency score based on the proportion of the words they used in all messages which appear in a 350,000-item list of English words from the Moby project, a public-domain lexicon-building project.¹⁷ The proficiency score is correlated with individual mean PA ($r=0.58$) and NA ($r=0.41$), which is to be expected since use of English affective words requires using English words in general. To correct for this, I limited the analyses to users who were proficient in English (as explained in detail below). Once non-proficient users were removed, the correlations between the proficiency

score and PA ($r=0.09$) and NA ($r=0.06$) were reassuringly small.

Figure 7 shows the distribution of English proficiency across the population. For residents of the English-speaking countries included in Figure 5, the proficiency score is unimodal with a peak at about 0.9, a steep decline below 0.9, and very few speakers below 0.8. (The proficiency score rarely reaches 100% because the English lexicon does not include items like typos, proper nouns, or some affixes.) For non-English-speaking countries, however, the distribution is bimodal, with a secondary peak at about 0.9 and a primary peak between 0.4 and 0.5.

In order to separate proficient from non-proficient speakers, I excluded those below 0.8 in all countries. I chose 0.8 based on the frequency distribution of proficiency scores in English-speaking and non-English-speaking countries (see Figure 7). In order to be certain that the results are not sensitive to the choice of 0.8 as the cutoff, I replicated all analyses using 0.9 as the cutoff, with no meaningful change in the results. Table 2 shows the attrition due to English proficiency.

Countries vary in numerous unmeasured ways besides linguistically (for example, culturally and socio-economically). This precludes the use of country as an explanatory measure for between-individual PA and NA variation. Instead, all measures rely on within-individual changes, which removes the between-individual differences that could be attributable to language proficiency. Since English proficiency is not expected to vary within individual, it cannot explain the PA or NA variation within individuals.

¹⁷ <http://icon.shef.ac.uk/Moby/mwords.html>

Table 2. The overall dataset contains a large number of relatively inactive users whose aggregated messages include too little information to provide robust measures of individual affect. We excluded these users, as well as those who we identified as non-proficient in English.

	Overall	Users w/ ≥ 25 Tweets	Users w/ ≥ 25 Tweets and EP ≥ 0.8
Tweets	526,304,834	509,691,124	413,843,285
Users	5,064,577	2,493,372	2,063,121
Mean (SD) PA/NA tokens per tweet	.75 (.99)	.76 (.99)	.88 (1.02)
Tweets with no PA/NA tokens	270,937,645 (51%)	261,494,571 (51%)	183,896,614 (44%)

Informal Language & Slang Use

Affect may sometimes be expressed in Twitter-specific informal/slang terms, or terms peculiar to on-line communication, either verbal or written. Since this study examines text from across the world, the data captures possible variations in the affect-laden slang terms specific to individual cultures. This analysis is therefore susceptible to measurement error to the extent that the LIWC lexicon does not include these items.

LIWC's homepage¹⁸ describes the sources of its lexicons as coming from lab studies in the U.S., Canada and New Zealand for people in "all walks of life," including students from elementary school to college, the elderly, and prisoners. Other sources include articles from *Science*, British and American novels, recordings of naturalistic conversation in public places, and weblog posts. The fact that these texts cover a variety of genres from American- and British-influenced sources increases confidence in its coverage, especially since English-speaking countries across the globe typically reflect British and American cultural influences, through mass media and foreign presence, both historical and contemporary.

Nevertheless, total coverage of all possible affective expressions is impossible.

Internet-specific slang that is not in the lexicon will go unmeasured. If the lexicon is more sensitive to the affective expressions of some cultures than to others, then their baseline affective levels will vary as an artifact of the lexicon rather than due to underlying differences in affect, a parallel situation to the English Proficiency measure described in the previous subsection. As noted, due to the potential for artifactual results, country is not used as a variable to explain between-individual affect.

¹⁸ <http://www.liwc.net/howliwcworks.php>. Accessed 29 April 2011.

CHAPTER 3

DEBT AND CREDIT IN AN ONLINE MICROLENDING MARKET¹⁹

Introduction

Access to credit is an important part of modern economic life. Home, car and student loans enable people to make life- and lifestyle-changing purchases while smoothing those large costs over long periods of time. Credit cards and other financial products enable people to smooth the costs of other consumption, or even to make ends meet. Commercial loans and lines of credit provide the capital businesses need to get started, continue operations, and invest in expansion.

Access to credit is fundamentally a problem of trust – providing money to another, with the trust that that party will be both willing and able to repay it in the future. Modern economies have many systems, technologies and institutions for establishing and maintaining this trust. Borrowers have stable identities and participate in systems of credit scoring, so that lenders may estimate the risk associated with repayment by a given borrower. At scale, debt may be packaged and traded like any other asset, enabling debt holders to manage their risk exposure through diversifying their holdings. Credit markets are subject to legal and regulatory requirements in lending practices, bankruptcy, credit reporting and beyond, that prescribe and proscribe the behavior of borrowers and lenders, yielding expectations about how they are to behave toward one another, and providing remedies and

¹⁹ Portions of this chapter are excerpted from a course paper for ILROB 7780, Spring 2009.

sanctions if one party should deviate.

Lenders are highly proscribed regarding the kinds of information they can use to make lending decisions. The Equal Credit Opportunity Act requires that lenders cannot use information like race, sex, marital status, religion or age to encourage, discourage, accept or reject a loan application, nor use that information in determining the interest rate, fees, or other terms. Factors like income and credit history may be considered, because those factors are deemed necessary for assessing repayment risk.

This paper examines a very different kind of credit market, an online *microlending* service Prosper.com that matches people seeking small loans – up to several thousand dollars – with people seeking to invest. Though the service’s operating model has undergone some changes over time (see section: “Prosper.com”), during the period of time under study, an auction mechanism enabled loan seekers to create loan requests (“listings”) and would-be investors would bid on that loan.

In brief, the loan seekers would create loan requests that included not only their basic financial information that a traditional lender would require – credit score, a measure of existing indebtedness, e.g. – but also descriptions of their reasons for seeking the loan, descriptions of themselves, their families and life circumstances, and often a photograph. Reasons are varied, but included starting small businesses, consolidating existing high-interest debt, car or home repair, or even buying Christmas presents for their grandchildren. Lenders would bid on portions of that debt. For example, a \$1,000 loan request might start accepting bids at 12%, and in a competitive auction might receive \$500 at 10%, \$300 at 9.5% and \$200 at 9.25%.

The reason for including such non-financial details, of course, is to attract

lender interest, either by providing information that might indicate folk trustworthiness or creditworthiness, or in some cases perhaps evoke sympathy. While traditional lenders could not include such information in lending decisions, Prosper lenders were under no such requirement, and could use any of this information to decide whether or not to bid on a listing, and what interest rate to offer.

This paper examines the ways in which borrowers present themselves to the market, and how the market responds. I examine how the personal factors borrowers provide, specifically their reasons for seeking the loan, affect their outcomes, both whether they are successful at having their listings funded, and at what interest rate.

Interest rate is an effective dependent variable since it functions largely as a measure of perceived risk. Though interest can also be thought of as the “rental fee” paid for the use of capital, investors of all levels of sophistication understand that risk and return are linked, investors demanding greater return in exchange for taking on greater risk (Derman 2013). The question, then, becomes: how do the personal details and reasons for loan-seeking affect perceived risk? If we can measure those factors’ impact on interest rate, we can measure their impact on perceived risk. Additionally, because sufficient time has passed, loan repayment data is now available as well; enabling “looking into the future” of each loan and observing empirically whether those personal factors indeed turned out to be good predictors of repayment, and therefore whether lenders’ perceptions of risk were accurate.

Though traditional lenders and investors are primarily interested in how *risky* the prospective borrower is, they are not necessarily interested in how *worthy* the prospective borrower is. Though some investors do practice “socially responsible

investing” and invest only in those businesses whose missions are consistent with their own values, for example “screening out” or avoiding tobacco companies or companies related to the military (Peifer 2011), investors typically have other dominating concerns, for example diversification and risk tolerance. For microloans, however, we can examine who gets funded – at whatever the interest rate – as a measure of the extent to which lenders are screening out those who are perhaps good investments from a narrowly economic perspective, but in some sense not worthy of the investment.

Disentangling these two mechanisms – worthiness and riskiness – presents a significant challenge. When a bid is placed, a clear action has taken place: the lender has deemed the borrower both worthy of the loan, and sufficiently low-risk at the price (interest rate) asked. However, when a bid is not placed, it is challenging to determine what happened, whether the borrower was considered unworthy of a loan at any price, or they were deemed too risk at the current price, but might have been a good investment at some higher interest rate.

The Morality of Debt

Like the relationship between economic and social behavior in general, the social and behavioral sciences have examined the relationship between debt and morality. Graeber (2011) focuses on exactly this relationship, describing a multitude of views thereon, including the “primordial debt” view, which casts debt as the “essence of society,” predating markets and governments, and characterizing the inherent interdependence people have on one another, with obvious and deliberate religious undertones. This debt, Graeber, writes, is inevitably appropriated by both

religions and states and used as a means of oppression and control, from ritual sacrifices to onerous transnational repayment schedules.

Weber (1904) identifies the relationship between the Protestant exhortation to work and resulting success in capitalistic endeavors and accumulation of wealth, explaining a cultural understanding of wealth as the just reward for industrious behavior and, conversely, of poverty and debt as the just punishment for lack of industry. The causal direction here is that industry → wealth and lack of industry → poverty and debt. Though in a strictly logical interpretation, the converse does not hold, that poverty and debt → lack of industry, Furnham and Rajamanickam (1992) show that people who adhere to the beliefs Weber characterized as the Protestant work ethic, also adhere to a “just world” theory, a folk theory under which outcomes, for good or for ill, are deserved by those who experience them. If outcomes are deserved, then the converse logical statement describe earlier *does* hold, and people’s behaviors – industrious or not – can be deduced by examining their financial circumstances.

Belief in the converse proposition has political and policy consequences. In a review of several books on American urban poverty, Wacquant (2002) points out that sociological studies of the urban poor, ranging from sidewalk vendors to single mothers, fall into the trap of treating their subjects as “paragons of virtue,” eliding their less savory behaviors (for example, crimes ranging from public urination, to serious physical violence) as a counterweight to their perceived political demonization, for example the “welfare queen” caricature of the Reagan era, given new life during the then-contemporary welfare reform enacted in the mid-1990s, a demonization which continues today. Undergirded by the belief that wasteful

behavior contributes to poverty, a variety of state legislatures since 2015 have passed or proposed restrictive laws regarding how public assistance funds can be used, from banning “steak and lobster” (Holley 2016) to restricting visits to movie theaters, swimming pools, and other recreational activities (Holley and Izadi 2015).²⁰

Folk beliefs about the relationship between consumption, lifestyle and financial situation were played for entertainment in the short-lived CBS reality television program, *The Briefcase*. In the program, two families who are struggling financially are each given a briefcase containing \$100,000 and invited to tour the other’s home, then asked to decide how much of the money in their briefcase to give away to the other (each family is unaware that the other is playing the game, as well. Structurally, the game is the Dictator Game – a player decides how to split the \$100,00 they have been given and the other player’s role is simply to accept. The point of the program, however, is a nearly voyeuristic trip into the personal lives of two families – their homes, possessions, bills, refrigerators – as the participants assess the “need,” i.e. the moral worthiness of the potential recipient, their circumstances, experiences and personal effects judged as praiseworthy (e.g. military service) or blameworthy (foolhardy business ventures). Like the microlenders we examine in this paper, the families of *The Briefcase* are asked to decide the financial fate of others, based on their own impressions of the moral status of their lives and lifestyles.

But, then, what are the circumstances surrounding people’s financial lives, and

²⁰ Multiple motives could simultaneously underpin these actions. For example, decreasing the desirability of a benefit or increasing the hurdles to receiving it might decrease its use, resulting in financial outcomes favorable to those proposing the restrictions, or to their political allies.

where are they spending their money?

Juliet Schor's (1999) *The Overspent American* analyzes why a large proportion of people at all income levels claim that their incomes barely cover their basic needs, and points to "competitive consumption" and the desire to increase or maintain status by achieving or exceeding the perceived material living standards of one's peers. Schor focuses on lifestyle goods and the signaling value they provide; in fact, the discretionary spend on these sorts of items, which constitutes the larger portion of her focus, amounts to just a fraction of household spend.

Data on consumer spending shows that most consumer spending falls into a few categories, dominated by housing, food, transportation, health care and insurance; these five categories comprise approximately 80% of household expenditures, with entertainment and "other" comprising the remaining 20% (Currier et al. 2015). Approaching the problem somewhat differently, a US Department of Labor report indicates that expenditures on "non necessities" has risen from about 20% at the start of the 20th century to 50% by the start of the 21st. Adopting Schor's frame of "competitive consumption," it is easy to see how social competition can occur even within these dominant categories – one might buy grander or more modest goods in every category – larger or smaller homes, luxury or standard cars, organic or conventional food, for example. It's not all designer purses.

The rise in spend on non-necessities over the course of the 20th century can be attributed to a variety of causes, not least the increase in income attributable to two-income households (women's labor force participation increasing from about 15% to about 45% over the century) with fewer children (family size decreasing from 5 to 2.5)

(Chao and Utgoff 2006). However, the first decade of the 21st century was marked by two recessions, and flat wage growth as compared to the strong wage growth of the late 20th century (Currier et al. 2015).

Amidst this flat growth, income volatility has increased; Pew reports that half of households experience wage changes of 25% in a 2-year period (Currier et al. 2015). Combined with being cash-strapped – most households have fewer than two months’ expenses in cash readily accessible – households have numerous opportunities to experience economic crises.

Economic crises can be costly. In her journalistic-ethnographic study *Nickel and Dimed*, Ehrenreich (2001) points out that “it is expensive to be poor.” Inability to pay up-front costs prevent people from achieving longer-term economic efficiencies, like buying in bulk, or annual apartment leases at lower rates than week-to-week ones. Also, minor setbacks lead to major ones in a financial domino effect – a broken-down car can lead to missed work, a lost job, and a lost home. Edin and Lein's (1997a, 1997b) studies of low-income single mothers also point out that low-skill jobs offer no sick leave and are subject to frequent layoffs, making these sources of income unstable.

And for middle class households, economic crisis may be no less avoidable. Though two-income households have led to increases in consumption and in disposable income, Warren and Tyagi (2003) point to a counterintuitive result: households that rely on two incomes, now have *doubled* their likelihood of economic misfortune, since the loss of either income can induce economic crisis. Further, sharply contrasting Schor’s diagnosis of “competitive consumption” as the source of

households' ills, Warren and Tyagi point instead to three primary causes of personal bankruptcy: divorce, job loss and medical bills.

We are left with contrasting narratives of households in debt. In one, discretionary spend is increasing as profligate households obsessed with competitive consumption purchase luxury goods on credit. In the second, an environment of stagnating wages leaves households vulnerable, with little capacity to absorb the shock of an unfortunate medical expense, driving them into series of cascading debts.

Among these households and everyone in between, the lender must ask themselves, who should I lend to? The high-earner whose preference for luxury brands left them temporarily in over their heads? Or the sober, thrifty low-wage worker struggling to afford medical bills? Who is more likely to repay the loan? Who is more deserving of the loan, and does it matter? Do I see aspects of myself in either of these people, and is my view of them, or my social obligations to them, shaded by that recognition?

In environments where informal lending, microlending or peer-to-peer lending have been observed, questions such as these have come into play, highlighting the social dimensions of this economic activity.

Borrowing in a Broader Economic Context

Conducting economic transactions within the context of social relations is a practice that is both old and ongoing. When uncertainty about exchange partners is high, choosing partners who are subject to existing and multifaceted social obligations is one strategy for ensuring cooperation (DiMaggio and Louch 1998; Simpson and McGrimmon 2008).

Geertz (1962) observed the existence of “rotating credit associations” all over the world. The rotating credit association functions as a social mechanism for enabling the members to engage in economic transactions by serially pooling resources for the benefit of each of the members in turn. If a rotating credit association had ten members and each contributed ten dollars, then a pool of one hundred dollars would be created, and it would be loaned to one of the members. At the next meeting, the pool would be loaned to a different member. This would continue until all members had had a turn at borrowing the pool. Geertz observes that the social function of the rotating credit association, strengthening social ties, is perhaps more important than the economic function of providing the members the capital needed to undertake some economic endeavor. In experimental settings, Cassar, Crowley, and Wydick (2007) found that personal trust and homogeneity, rather than general societal trust, were important factors in ensuring repayment.

Like rotating credit associations, investment clubs are organizations that are based on social ties, but bring people together for the purpose of pooling funds in order to achieve an economic objective. Harrington (2008) conducted an extended ethnography of multiple investment clubs, in which individuals would pool investment funds, then collaboratively make investment decisions. While any member could invest their portion of the funds individually, pooling not only enabled diversification of investments and allowed members to potentially benefit from one another’s views, but also turned investing into a group activity and therefore a social experience.

Outside of social contexts, deciding who to trust has developed into a formalized process, and Fourcade and Healy (2013) suggest that the pervasiveness of

scoring people both within and outside of narrowly-construed financial contexts is tantamount to a class structure and has significant effects on people's life chances; relatedly, Poon (2009) tracks the role of the FICO score in the use of mortgage lending. Stearns (2011) catalogues the development of the general purpose credit card, from merchant-specific payment cards used at gas stations and department stores, to category-specific cards like Diner's Club, which were not direct sources of profit but rather generators of increased customer loyalty and therefore customer spend, and which had already offered consumers a mechanism for buying on credit. For these early payment cards, the creditors were the individual merchants, rather than a financial institution, and payment was required in full at the end of a billing cycle, rather than being part of a revolving line of credit. Revolving lines of credit rely on a comprehensive risk calculation of the kind FICO provides and enables the classification systems Fourcade and Healy (2013) and Poon (2009) describe. In contrast to the presence of developed and formalized credit scoring methods in the U.S., Guseva (2008; Guseva and Rona-Tas 2001) note that Russia's lack of such a system held back the development of a credit card market and, consonant with the patterns observed by DiMaggio and Louch (1998), instead resulted in financial institutions relying on personal ties and trust when making credit decisions.

Over the period Stearns (2011) describes, the credit card has become a dominant means of purchasing both for convenience and out of necessity for people of all age groups in the U.S. A study by Sallie Mae (Anon 2009) points out that, at the time of the study in 2008, 84% of college students had at least one credit card, and 40% used their card to finance purchases they knew they did not have the money to

pay for. Bar-Gill and Warren (2008) point out that financial products – like credit cards, but also mortgages and other secured and unsecured loans – can be confusing, sometimes deliberately so, and liken them to dangerous products of the sort that might be regulated by the FTC or CPSC.²¹ However, decisioning for these traditional financial products relies heavily on the FICO score, and for the potential borrowers with the lowest credit scores, these products might not be available, preventing access not just to the financial product, but to the things those financial products buy, creating the cumulative disadvantage that Fourcade and Healy (2013) describe.

If people cannot borrow through traditional means, they may turn to alternative financial services, like payday lenders. Though controversial, payday lenders provide access to credit who either do not have a relationship with the mainstream banking system, do not qualify for additional credit, or whose preferences or needs aren't met there.²² Payday loans can be quite costly, compared to traditional financial products, with high origination fees and interest rates that are equivalent to effective APRs of over 400%; further, when an individual cannot repay a loan, it is typical to roll the loan over into a new loan, with a new origination fee, and so on, leading to rapidly spiraling debt. However, the fees associated with a payday loan may be lower than the fees associated with nonpayment of the utility bill for which the borrower had sought those funds. Additionally, when payday lenders are unavailable, it has been shown that borrowers for whom that is the choice of last resort then resort to even less

²¹ Their findings formed the basis for the Consumer Financial Protection Bureau, of which Warren oversaw the development as first a Presidential advisor and then as Senator from Massachusetts.

²² For example, in some circumstances obtaining cash immediately is often preferable to waiting for a

favorable lending via pawn shops (Bhutta, Goldin, and Homono 2016).

Sharing Economy

Microlending arises as a form of online exchange as part of a broader set of trends that are often captured by the phrase, “sharing economy” which includes examples from varied industries, such as car “sharing” services Uber and Lyft, “home sharing” services like AirBNB and Couchsurfing, and casual labor services like the helper service Taskrabbit and food delivery services like Postmates and Seamless.

The phrase itself is a misnomer, as what is taking place is not typically thought of as sharing, but rather market-making, turning individuals into sellers of goods or labor, in one-shot transactions brokered by an internet-based service. Uber drivers are “sharing” their car in the sense that passengers are riding in the drivers’ personal vehicle, but this is not sharing in the conventional sense. Rather, Uber the service acts as a market maker, connecting individuals who can sell their time, driving labor and vehicle use to people who would like to pay for a ride.

In the case of Uber and many others, the market maker controls access to the market on both sides, for the purposes of managing both risk and prices. Barriers to participation for sellers such as standards for car cleanliness, driver background and ongoing driver rating serve to reduce uncertainty on the buy side. Allowing or disallowing entrants and continuously resetting prices stimulates the supply or demand for rides as needed. Likewise, AirBNB matches people who have space to rent with people who need a place to stay, and control entry into the market in order to reduce

deposited check to clear, even if the total cost for the former is greater.

the risk to both buyers and sellers – notorious cases of personal crimes by both seller and buyer have been in the media, as have stories of rented homes being trashed or used as bases for illicit activities.

A closely related term to the sharing economy is the “gig economy,” characterizing the casual labor associated with jobs like Taskrabbit, as well as Uber and others. These jobs make economic activities out of many of those things that could once have actually been characterized as sharing – giving a friend a ride or letting one “crash” at your home, or running an errand on their behalf. In the sharing economy, one does not receive in exchange for participation gratitude or deeper embeddedness in a social network bonded by ongoing reciprocal exchange; one receives a 1099.

It is worth noting that these activities aren’t completely new; for nearly two decades, eBay’s online auction site created a market for generic goods, matching people with things to sell with people interested in buying them, monitoring participants indirectly through a system of feedback from transactors (Kollock 1999), and allowing prices to emerge through an auction mechanism.

As AirBNB turns homeowners into hotel operators and Uber turns car owners into taxis, Prosper turns people seeking to borrow money into bond sellers and people seeking to lend into financial services institutions. Other sharing economy-related businesses likewise seek to match people needing money with those willing to invest – or in some cases, donate -- include Kickstarter, GoFundMe and LendingClub, the latter most closely related in concept and function to Prosper.

A third term, the “peer-to-peer economy” most closely characterizes many of

the businesses here, drawing an analogy to peer-to-peer networks in which individual nodes communicate with one another directly rather than communicating only as clients in relation to a central server. However, while individuals do comprise both the buyer and seller pool, the intermediaries do more than matching, and act more as bookmakers, taking both sides of the economic transaction. Drivers do not sell rides to passengers; passengers purchase rides from Uber, and drivers sell rides to Uber. Prosper lenders do not lend directly to borrowers; lenders purchase a note (financial instrument) from Prosper, who in turn issues a loan to the lenders.

The novel models of organizing and operating markets demonstrated by these companies are due to a common set of underlying technological and social changes.

One of these changes is massive micro-participation. While a Prosper borrower may seek to borrow of contributions from many small lenders. An Uber driver need not drive full-time – and, indeed, many do not, but rather do so as a part-time job. Drivers may drive only when rates rise due to increased demand, or under whatever circumstances they might choose. Likewise, riders purchase rides on a per-ride basis, so there are no fixed costs involved. Entry and exit into the market is relatively easy and because participants may participate at whatever level of intensity they might choose.

Second, the efficacy implications of crowdsourcing. Since Prosper and related services like Kickstarter and GoFundMe are funded by many small, fractional loans, the relationship between inputs and outputs is smooth, in contrast to scenarios in which all-or-nothing decisions must be made. Borrowing is not dependent on a single yes-or-no decision from a loan officer – or a statistical model the loan officer invokes

– but rather on the independent decisions made by potentially hundreds or thousands of individual lenders, making microlending an attractive borrowing option for those for whom conventional credit is unavailable. Signing a roommate to a lease is a large commitment, but renting a room on AirBNB is a series of lower-stakes smaller commitments.

Third, peer-to-peer economies operate with relatively low information costs. Listings on market-oriented sites like AirBNB, Prosper, and the like contain not only information about the room, loan or item being listed, but the user profile of the person on the other side of the transaction, which may contain personal information, and also their behavioral history including the details of past transactions, and reviews from others who they have transacted with before. Building a reputation for cooperative behavior takes time and participation in many previous transaction, and so the cost of bad behavior is increased, since tarnished reputations cannot be so easily abandoned (Friedman and Resnick 2001). When participation is tied to offline identities, then online behavior is even more closely tied to offline identity, further increasing the cost of bad behavior. While users may gain the ability to use web search and social networking sites to get even more details about their transacting partners, service operators may collect social security numbers, driver's licenses, and home addresses in order to perform background checks or enable recourse to law enforcement if the need arises. Lending someone money, or getting in their car or staying in their home, are activities that place individuals in vulnerable situations, and in order for market makers to build trust in the market, they must also build trust amongst the participants.

Finally, a veneer of personal connections overlays the participants' interactions

with the market. Loan request descriptions are written in the first person, addressing potential lenders directly; a characteristic example reads: “*My husband and I need a little help. Everything started when I got laid off from my job in May of 2003... I just need someone to have some good faith in some good people who have had some bad luck. Thanks for reading this far. Hope you can help!*” Though borrower and lender share no social relationship, the language of help, gratitude, and so on, implicitly leverage the commitments that might otherwise be present in conventional social ties.

Prosper.com

Prosper.com was among the earliest and, for a time, the most prominent of web services in a category called *peer to peer lending*, and might today be considered a *fintech* company, or one seeking to provide new or better financial services through the use of technology. Prosper’s business model has changed over time, but for the period under investigation, Prosper functioned as a market maker and an auction site, matching people who would like to borrow money with people who would like to invest money. Prices (i.e. interest rates) are established through an auction process, whereby potential lenders bid on the auctions initiated by potential borrowers. As such, it has been called an “eBay for loans” (Hof 2006).

Consider the following hypothetical, but typical scenario:

- Alice is a 23 year-old new graduate and wants to borrow \$5000 to pay off a credit card balance. She creates a loan listing on Prosper called “Help me consolidate my debt!” and describes the debt she ran up in college, as well as her income from her new job. The listing includes her credit rating and

loan history. She decides the highest rate she'll accept is 14%.

- Betty visits Prosper, hoping to invest some money at a favorable rate. The market is down, and her CDs were earning only 3%. She finds Alice's

The screenshot shows a Prosper.com loan listing. At the top, the Prosper logo and navigation menu are visible. The main heading is "To pay off my Credit Card" with a listing ID of #167079. The listing summary shows a bid of \$10,000.00 at a 10.98% rate, with a "Bid Now" button indicating the bidding has ended. A "Borrower Info" section includes a profile picture, name (chicoblee), location (CANDIGA PARK, CA), and statistics like 0 friend bids, 0 questions & answers, 0 friends, 0 verified, and 1 loan total, 1 active. A forecast chart shows the loan's funding progress over 7 days. The "Credit Profile" section displays an A credit grade, 20% debt to income ratio, and various financial metrics such as delinquencies, credit lines, and revolving credit balance. The "Description" section contains a free-text explanation of the loan's purpose and the borrower's financial situation. At the bottom, a "Bid History" table lists all bids received, including bidder names, rates, amounts, and winning statuses.

Bidder / Relationship	Rate	Amount Bid	Winning	Status	Bid Date (PT)
OPeMo	10.98%	\$100.00	\$100.00	✓	Jul-17-2007 6:54 PM
ellidre	10.98%	\$129.13	\$129.13	✓	Jul-17-2007 6:52 PM
minista	10.98%	\$200.00	\$200.00	✓	Jul-17-2007 6:50 PM
Oblicc	10.98%	\$100.00	\$100.00	✓	Jul-17-2007 6:50 PM
banker799	10.98%	\$50.00	\$50.00	✓	Jul-17-2007 6:50 PM
PHANTOM4751	10.98%	\$101.00	\$101.00	✓	Jul-17-2007 6:44 PM
BenniG	10.98%	\$50.00	\$50.00	✓	Jul-17-2007 6:37 PM
vitedfish	10.98%	\$100.00	\$100.00	✓	Jul-17-2007 6:31 PM
Ernie100	10.98%	\$50.00	\$50.00	✓	Jul-17-2007 6:03 PM
gdqed	10.98%	\$75.00	\$75.00	✓	Jul-17-2007 6:02 PM
richnow	10.98%	\$50.00	\$50.00	✓	Jul-17-2007 5:57 PM
hammockman	10.98%	\$50.00	\$50.00	✓	Jul-17-2007 5:21 PM
gboomer2611	10.98%	\$50.00	\$50.00	✓	Jul-17-2007 5:13 PM
shahler	10.98%	\$55.42	\$55.42	✓	Jul-17-2007 5:06 PM
KnightKSIJ	10.98%	\$150.00	\$150.00	✓	Jul-17-2007 5:04 PM
marlover	10.98%	\$54.00	\$54.00	✓	Jul-17-2007 5:01 PM
loriel	10.98%	\$50.00	\$50.00	✓	Jul-17-2007 4:18 PM
boardgame madness	10.98%	\$59.09	\$59.09	✓	Jul-17-2007 4:04 PM
tss	10.98%	\$100.00	\$100.00	✓	Jul-17-2007 3:58 PM

Figure 8. A typical Prosper.com loan listing. This listing includes a photograph, detailed economic information ("Credit Profile") and a borrower-provided free-text description of their reasons for borrowing and their other circumstances ("Description"). The list of bids received is shown at bottom.

listing and decides to lend Alice \$50 at a rate of 13%, a sizable difference from her old CD.

- Carol visits Prosper too, and also sees Alice's listing. She thinks Alice is a good credit risk, and so will lend her \$100 at a rate of 10.5%.

Figure 8 shows a typical listing.

If Alice's loan doesn't receive enough bidders (the bid amounts total less than the \$5000 she sought), then the auction will end; she will not receive the loan, and no money will change hands. However, if the total of the bids exceeds the \$5000 she hopes to borrow, the lenders who bid the lowest interest rate will win.

In this way, borrowers receive the most favorable rates the market will offer them. Prosper is a one-way market; the lenders can choose which auctions to bid on and therefore which borrowers to lend to. However, the borrower has no choice but to accept the lowest bids that are made. After the auction is completed, there is no further contact between borrower and lender; in fact, it is prohibited. Prosper loans are fully-amortizing loans with a fixed 36 month term, though borrowers may repay early. All loans are made directly to Prosper, and after deducting its fee, payments are divided proportionately among the several lenders.

Prosper members have the opportunity to form and join groups, which are most often organized around some topic, including a religious or ethnic identification, geographic region, profession, hobby or social activity, or life circumstance such as disability. While these groups do not operate as rotating credit associations *per se*, some similar features exist: members of the group are often publicly warned that all

borrowers are expected to be trustworthy and to repay their loans and, in some groups, members are encouraged to bid on the loans that other members seek, so as to “support our community”. Groups have “leaders” who start the group and recruit new members. In some cases the group leaders screen prospective members for creditworthiness (e.g. through a telephone interview) and/or charge a “group leader reward” of up to 1% of the loan amount. Groups have titles and descriptions explaining what sorts of members are sought, but not all groups are tied to substantive identities. While some groups are for identities like Christians or firefighters, other groups have descriptions like “people who want to borrow money” or catchy ones like “the financial freedom group” – that is, a group in which there is little distinctiveness between members and nonmembers. Groups may belong to a number of categories, which are organized into a hierarchy of category types, as shown in Table 5.

History

Prosper began operating in early 2006, using the auction model described above. From 2006 onward, Prosper received mainstream press emphasizing its personal nature, and potential to change banking (Kadet 2007; Steelman 2006). It also developed an active investor community (Anon 2015), networks of blogs and sites on which lenders wrote about their investing experience, provided tips and best practices, and conducted data analysis on the datasets of historical market behavior that Prosper made available to the public. These investment communities are reminiscent of the investment groups that arose a decade earlier, in which people would come together to share the research they had conducted, describe their experiences, and in some cases invest together from pooled investment funds (Harrington 2008).

Though marketed as peer-to-peer loans, the Prosper loans were legally structured such that borrowers and lenders had formal relationships only with Prosper, not amongst themselves; Prosper would lend to the borrowers, and borrow from the lenders, providing the former with a personal loan and providing the latter with securitized debt. However, this structure put Prosper in the position of being a securities dealer, a position for which it did not have a license. On October 16, 2008, Prosper received a Cease and Desist letter from the Securities and Exchange Commission (SEC) indicating that it was in effect selling securities without a license, and was forced to discontinue the practice (Anon 2008). Further, a class action lawsuit was initiated against Prosper, alleging that all lenders who were active between January 2006 and October 2008 were harmed because of this unlicensed activity.²³

Prosper briefly ceased accepting new borrowers and lenders in October 2008, in order to register with the SEC and alter its business model. When it began operating again in 2010, the auction model was replaced by a proprietary model that set fixed interest rates (Lieber 2011). Today, microlending remains a niche industry, dominated by Prosper competitor Lending Club (Anon 2014). Prosper continues to be active, though its future may be considered uncertain, indicated by its layoff over a quarter of its staff (Renton 2016) and closure of its secondary debt market .

Market Conditions

This analysis focuses on auction performance. Accordingly, in light of

²³ The details of the class action lawsuit may be found at <http://www.prosperclassaction.com/>.

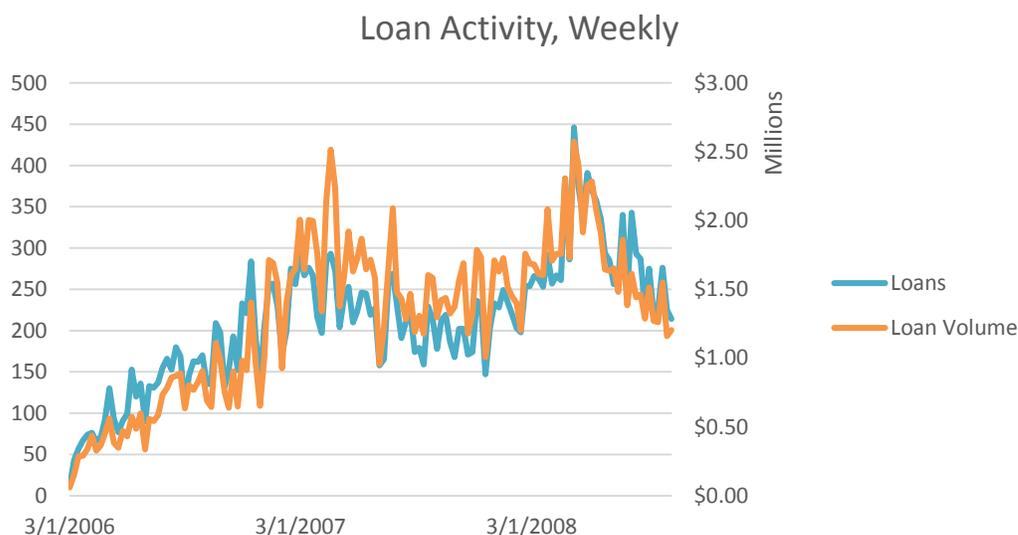


Figure 9. Prosper's weekly loan activity, March 2006 to September 2008.

Prosper's changing business model, I include only that time period in which Prosper ran auctions, starting with March 1, 2006 (the first day over 100 listings were created, about two months after the company began operations), and concluding on October 16, 2008, the day operations stopped due to the SEC Cease and Desist order.

As shown in Figure 9, Prosper grew steadily in terms of loans issued through early 2007 and was flat to declining through the year, peaking in mid-2008 and

Table 3. Counts of Activities on Prosper

<u>Statistic</u>	<u>Value</u>
Listings	341,481
Completed	28,976
Expired	191,149
Withdrawn	114,771
Earliest Listing	3/1/2006
Latest Listing	10/15/2008
Users who sought loans	154,307
Users who placed bids	57,394
Total bids	6,002,467

Table 4. Count of Listings on Prosper by Number of Bids Received. Most listings received five or fewer bids.

Bids	# Listings	% Listings	% Listings, cum.
0	159,462	47%	47%
1	60,264	18%	64%
2	23,240	7%	71%
3	12,605	4%	75%
4	8,219	2%	77%
5	6,155	2%	79%

declining until it stopped operating in October of that year. Other metrics had similar shapes, including number of bids and bidders. During the period under study, over 340,000 listings were created by over 154,000 users, and nearly 29,000 of those listings were funded as loans (8.5%). Table 3 provides additional statistics.

Prosper is a clear winner-take-most market, with a small proportion of loan

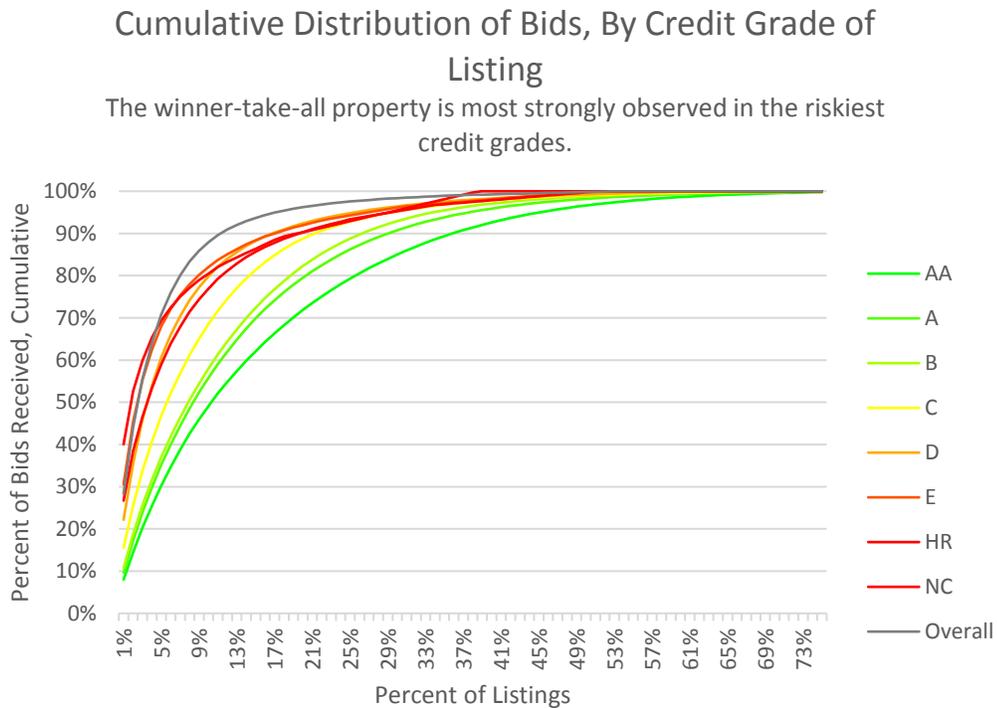


Figure 10. Prosper bids disproportionately go to a very small number of listings, especially among the riskier credit grades.

requests attracting the vast majority of bids. 47% of listings receive no bids, and 79% of listings receive five or fewer bids (Table 4). As shown in Figure 10, overall about 90% of bids are made on 10% of the listings; this property is most strongly observed in the riskier credit grades, the high-risk (“HR”) and no-credit (“NC”) credit grades.

This is likely a result of the fact that the market is full of risky borrowers, people who may be visiting Prosper as a lender of last resort, finding themselves unable to obtain credit conventionally.²⁴ While consumers with credit scores under 600 (categories HR and E) make up 61% of the listing pool, they make up only 24% of the funded loans. Conversely, borrowers with credit scores over 720 (categories A and AA) comprise a similar proportion of the loans (22%), but comprise only 7% of the listings. But the former pay an average of 26% interest, while the latter typically pay only 10-13%.

As Prosper’s popularity grew, so did the demand for new debt, with the ratio of bids to listings increasing from 5-10 throughout most of 2006 to 20-25 by 2008 (Figure 11). At the same time, the rate at which high risk borrowers were being funded decreased, perhaps due to early investors’ bad experiences, from comprising nearly half the funded loans in the end of 2006, to only 10% by late 2008, the mass of bids moving to the relative security of mid-grade (B, C, D) borrowers whose moderate credit scores (600-720) provided a different risk profile (Figure 12).

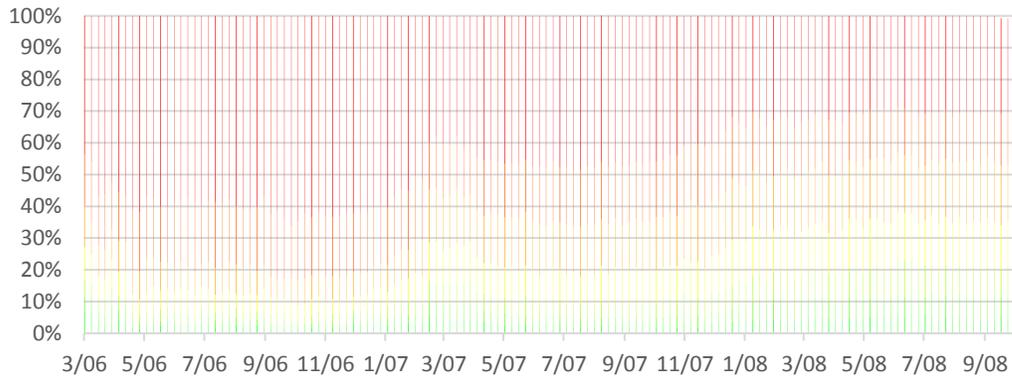
²⁴ Prosper is not intended for or used by only those who lack access to mainstream sources of capital. For example, many of Prosper's borrowers have high credit scores and incomes, and seek loans from Prosper in order to begin or expand small businesses.



Figure 11. Weekly investor demand, as measured by bid-to-listing ratio.

It has been shown that, while investing in higher-credit borrowers has a positive expected return, investments in lower credit grades has a negative expected value (Chen et al. 2008); despite paying high interest rates, low credit rating borrowers default in aggregate to a sufficient extent that the lender will lose money in expectation. As nearly all loans are in good standing after three months, it is unlikely that there is a significant proportion of fraud. Rather, it is more likely that failure to repay is due to inability, rather than malfeasance. After six months, the riskiest credit grades begin to show some signs of inability to pay. Loans' likelihood of being in good standing (paid or current) at the end of their repayment period decreases sharply with credit grade.

Listings' Credit Grades, Weekly



Loans' Credit Grades, Weekly

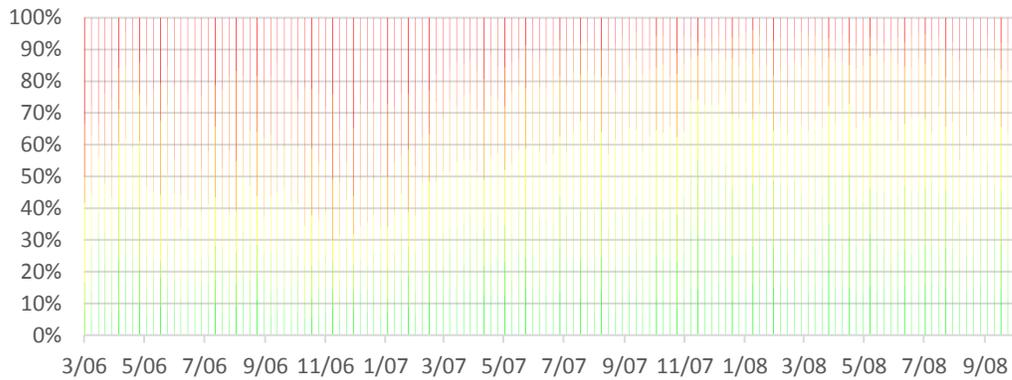


Figure 12. Proportion of listings (top) and loans(bottom) by credit grade and week.

Method

Previous work has shown that prosper operates like a traditional credit market in many ways (Chen et al. 2008; Kumar 2007), in that the interest rate a borrower pays is associated with their credit histories. I therefore begin by establishing baseline models that capture three outcomes – who is funded, what their resulting interest rate is, and who defaults – using only the financial data available: credit grade, debt level, loan size, and so on.



Figure 13. Across all credit grades, nearly all loans are in good standing after three months. Over time, borrowers in riskier credit grades experience many more defaults.

Next, I include additional data elements, including social elements like group membership and photograph use.

Including a photograph is not strictly required, in the way that economic information like credit grade is. Nevertheless, 51% of listings and 66% of loans do include some image, typically a photograph but sometimes a logo, or even an inspirational image. By including some image of their own choosing, the would-be borrowers may express some aspect of their identity, and put a human face (literally or metaphorically) on their loan application.

Previous work has shown that the contents of a photo in an online auction or sale listings can have noticeable effects on the price the borrower is able to fetch for their goods. Pope and Sydnor (2011) demonstrated that Prosper listings showing black borrowers were funded 25-35% less than white borrowers and, when they were, paid higher interest rates; however, they suggest that these borrowers' higher default

rates, identified using loan repayment data, may be an economic rather than a “taste-based” response. Drawing on the audit studies that showed that names with strong race connotations affected, among other things, job applicants’ likelihood of receiving an interview (e.g. Bertrand and Mullainathan 2004), studies of eBay auctions have shown that photos indicating the seller is black received “fewer and lower offers” (Doleac and Stein 2013), and resulted in 20% lower purchase prices (Ayres, Banaji, and Jolls 2015). Other eBay-focused studies have found similar effects for women as compared to men (Kricheli-katz and Regev 2016). These effects, predictably, extend beyond eBay – rental prices on AirBNB vary by 12% between black and white landlords (Edelman and Luca 2014). In the field of computer-mediated communication more generally, though it was once hoped and believed that anonymity online would result in greater equality due to the lack of clear racial or gender cues, in fact research has shown that the opposite may occur. Postmes and Spears (2002) demonstrated in laboratory experiments that deindividuation, or the inability to distinguish one individual from another – as might be the case in an online environment with low communication bandwidth, where real names and other personal identifiers or histories are not present – might in fact increase stereotype activation. One might therefore expect online lending or selling environments to exhibit *more* rather than *less* stereotype-induced discrimination.

Prosper members, both borrowers and lenders, have the opportunity to form and join groups. Participating in groups is somewhat common; 27% of listings and 38% of loans are affiliated with groups. These groups may be organized around some shared identity, including religious or university affiliation, occupation, disability or

Table 5. Prosper Group Membership Statistics

<u>Group Category</u>	<u>Group Count</u>	<u>Listing Count</u>	<u>Member Count</u>
Business & Professional	2,317	73,939	54,854
People & Lifestyle	745	48,140	35,211
Education & Alumni	715	37,873	23,913
Religion & Spirituality	304	23,915	18,419
Hobbies & Clubs	469	25,751	17,937
Military	279	17,757	14,888
Regional	559	21,420	13,933
Civic & Political	260	12,454	9,629
Science & Health	225	6,410	4,465
Art & Culture	233	2,990	3,665
Non-Profit	258	2,795	3,441
Ethnicity & Nationality	204	3,849	2,982
Sports & Recreation	256	2,817	2,187

other life circumstance, or even a favored hobby or recreational activity. Other groups are not based on shared identity, and instead serve only as a vetting mechanism. Table 5 shows membership and activity statistics by type of group.

Groups perform a variety of functions, including requiring member vetting by a group leader, or encouraging bidding on one another's listings in order to "support the community," echoing the behavior of conventional rotating credit associations. Group leaders will in some cases charge a fraction of a percent of each loan as a fee. This may be an economically beneficial outcome in some cases; if a group can filter out high-risk borrowers and attract additional lenders, then borrowers' interests rates will be driven down via the increased demand brought about by increased competition and the perceived lower risk of the borrower pool.

The positive in-group bias that is generated even from nominal group affiliation (Tajfel and Turner 1986) may be a catalyst for bidding on group members' loans. Since group identification generates loyalty, self-sacrifice and willingness to

pay group costs (Brewer and Silver 2000), lenders may bid even on those loans that are not perceived as economically viable, and in turn, since group identification also generates decreases in non-cooperative behavior (Tyler 2003), borrowers may exhibit greater effort to repay when their loan is funded by fellow group members.

Though there is likely to be significant heterogeneity in the effects of photos and groups depending on the content of the photo and the characteristics of the group, full content analyses of photos and groups is beyond the scope of this project. Instead, as further described later, I include indicator variables for the presence or absence of photographs and group membership in order to, in a limited way, account for their effects, while focusing attention elsewhere, namely, on the borrower's prose loan descriptions.

The final set of models builds on the previous ones by investigating the effects of the borrower-written listing description on listing and loan outcomes. In order to turn the free-response prose text into numerical formats amenable to inclusion in statistical models, I apply a number of text analysis methods ranging in complexity from simple keyword counting to using words' distributions to probabilistically group them into coherent topics or map them into a semantic space. These methods are described in greater detail in the next section.

Modeling Approach

I estimate the models using multiple approaches, starting with the approaches and evaluation techniques familiar to quantitative sociological research and then other approaches. For example, an OLS regression model may be evaluated by reference to the R^2 value and effects of independent variables by reference to the p values

associated with the models' coefficients. However, I will also use other approaches, such as ensemble learning with boosted decision trees, evaluating model quality based on prediction error on an out of sample dataset; the effects of individual inputs can be understood by changes in error metrics when those inputs are excluded, or changes in the target when those inputs are varied, for example using partial dependence plots (Hastie, Tibshirani, and Friedman 2009).

Data Description

The basic model includes only economic inputs and some controls that account for byproducts of the Prosper system, for example the duration of a listing in days.²⁵

The inputs included are:

- Credit Grade (AA, A, B, C, D, E, HR, NC)
- Amount Requested (\$1000's)
- Is Borrower Homeowner
- Debt To Income Ratio (plus associated binary inputs for "unknown" and "excess")
- Listing duration (3, 5, 7, 10 or 14 days)
- Quarter (11 quarters, each covering 90 or 91 days from 3/1/06 – 10/15/08, except the 11th quarter, which covers only 45 days. Since "NC" loans are present only in quarters 0-3, the quarter 4-11 indicators are dropped for NC-grade-only models.)

Credit Grade is converted into a series of binary inputs, one for each credit grade ("one-hot encoded"). For some models, grade B is dropped to avoid multicollinearity, but all are included for tree-based models.

Listing duration is converted into a series of binary inputs as well, but is "cascaded" in order to take into account the ordering effect of the lengths. For example, a listing lasting 7 days has both the "5 day" and "7 day" inputs set to 1, and a

²⁵ Listings that last longer have greater opportunity to be seen by lenders, receive more bids, and therefore likely have a greater likelihood of being funded, and at lower rates.

listing lasting 14 days has all inputs set to 1. In this way, for example, the “10 day” input measures the effect of the additional 3 days of availability, as compared with a 7 day duration.²⁶

The debt-to-income ratio is measured as a percentage, from 0 to 100. For some cases (8.1%), the debt to income ratio is unknown. For these cases, the debt-to-income ratio is modeled as 0, with a dummy variable “DTIUnknown” set to 1. For a small number of cases (4.1%), the debt to income ratio exceeds 100%, in some cases going up to 1000% or greater. It’s not always clear that these measures are accurate, and they are small in number. For these cases, debt to income ratio is top-coded at 100%, and a dummy variable “DTIExcess” is set to 1.

Quarter is included as a series of one-hot encoded binary inputs (Quarter 0, March-May 2006, is dropped as needed) in order to capture secular change in the Prosper market. As described earlier, the likelihood of a high-risk listing being funded was much greater in Prosper’s early days than toward the end of the timer period being examined.

These representations of the economic data are consistent throughout all models, unless otherwise indicated.

Beyond the basic model, I include, in sequence, two additional indicator variables, “has_photo” and “has_group”.

Finally, building on the previous models, I consider various approaches to

²⁶ As duration measured as a number of days, another alternative encoding here would be simply as a numeric input. However, there is likely a nonlinear effect, in that there is likely diminishing benefit to keeping a listing open longer.

including information about the textual content in the models. The methods vary, but the overall objective is the same – to represent a body of text in terms of a fixed number of numeric measures that characterize some attribute of the text that might be causally related to something else. For example, the most simple method one might think of is “length,” since one might hypothesize that the number of words in a document is a good proxy for how much effort was invested in producing it, and therefore a potentially valuable predictor of likelihood to repay a loan. Other simple methods include -- but are not necessarily performed here -- average word or sentence length (more complex words or sentences being indicative of greater education) or number or rate of spelling errors (more errors being indicative of carelessness or incompetence and therefore likelihood of default); more complex methods might include rates of words associated with various topics or themes, indicating whether the writer has concerns related to those themes.

In this vein, I apply four text analysis methods, two corpus-based (LIWC and ANEW), and two probabilistic topical approaches (LDA and word2vec).

The first text analysis model includes simple word counts using the Linguistic Inquiry and Word Count (LIWC) package, which was also used in Chapter Two. This package contains 64 lexicons comprising 4,487 words and word stems, enabling analyses like counting the fraction of words in a document that correspond to a given lexicon (Pennebaker et al. 2001). Of the 64 lexicons in the package, I create continuous variables for eleven: negative emotion, positive emotion, future, past, health, home, leisure, money, achievement, religion and work. Each listing’s measure for each lexicon is the fraction of words (or word stems) that appear in that lexicon.

For example, a listing with a LIWCwork score of 0.05 indicates that 5% of the words in that description appeared in the work lexicon.

The second model uses the Affective Norms for English words corpus, which measures 1,034 words along three dimensions: arousal, dominance and valence (positivity / negativity) (Bradley and Lang 1999). These words were rated by subjects on a 1-9 scale; the resulting mean is used. Each listing's measure for each of the three dimensions is the mean of the in-vocabulary words' mean score on that dimension; out-of-vocabulary words are ignored.

The third model uses Latent Dirichlet Allocation (Blei et al. 2003) to learn “topics” from the text. Each of N topics (the N in question being chosen in advance) is represented as a probability distribution over each word in the corpus. In turn, each of the documents – in this case, loan descriptions – is represented as a mixture of topics. A document is not “about Topic 1” to the exclusion of all the other topics, rather its membership in topics is expressed as percentages, for example a document may be “80% about Topic 1, 3% about Topic 2, 5% about Topic 3 and 12% about Topic 4.”

The LDA approach requires that the modeler choose some parameters in advance. These include number of topics and vocabulary size; each should be large enough that it captures the important variation in the content, but not so large as to include irrelevant data or blunt the model's understanding through forcing excessive granularity. Since exhaustive search over these parameters is infeasible, the modeler necessarily has to make some compromises. For vocabulary selection, I first cleansed the text of punctuation, converted everything to lower-case, and removed the English-language stop words as given by the python nltk package, as well as nonce words and

numeric strings (e.g. “1997” or “203.25”). No stemming is applied. After this process, 124,261 unique tokens remained in the vocabulary (out of an original 310,926 raw tokens). I experimented with this vocabulary size, as well as a vocabulary truncated to the 20,000 most common tokens (not including the stopwords). For each of the two vocabulary sizes, I ran LDA topic generation for topic counts ranging from 5 to 75, in increases of 5; each experiment ran for 200 iterations.²⁷ In general, the suite of experiments with the larger vocabulary did not exhibit any improvement over the truncated vocabulary, so I eliminated the former. Among the 15 experiments with the 20,000-item vocabulary, model performance increased with topic count, but with rapidly diminishing returns after about 25 topics. Since each topic would be represented as an input in downstream classification models, it would be advantageous to select only as many topics as would provide better topic information, and so I selected 30 as the topic count to use in subsequent modeling. Example words from each topic is shown in Table 6:

Table 6. Top words per topic generated using Latent Dirichlet Allocation.

Topic	Top Words
1	real (2.10%), estate (1.91%), property (1.77%), business (1.43%), mortgage (1.32%), cash (1.04%), investment (1.00%), market (0.94%), rental (0.89%), house (0.75%), properties (0.75%), equity (0.74%), sell (0.61%), purchase (0.56%), used (0.49%), funds (0.46%), flow (0.45%), per (0.43%), sale (0.42%), homes (0.40%), use (0.38%), value (0.36%), sold (0.34%)
2	card (1.52%), interest (1.51%), high (1.02%), consolidate (0.70%), much (0.67%), every (0.63%), making (0.63%), never (0.61%), n't (0.52%), late (0.52%), rate (0.51%), minimum (0.44%), 'm (0.43%)
3	children (2.34%), family (1.77%), daughter (1.32%), son (1.30%), old (1.24%), husband (1.16%), mother (1.09%), child (1.06%), single (0.99%), kids (0.97%), life (0.91%), hard (0.79%), support (0.78%), school (0.77%), wife (0.74%), care (0.73%), married (0.64%), mom (0.60%), father (0.52%), trying (0.52%)
4	prosper (3.64%), score (1.15%), please (1.13%), listing (1.10%), questions (0.83%), rate (0.79%), see (0.71%), interest (0.69%), thanks (0.69%), report (0.68%), rating (0.63%), first (0.59%), lenders (0.59%), last (0.59%), request (0.56%), account (0.53%), lender (0.50%), feel (0.49%), funded (0.46%), low (0.45%), amount (0.45%), late (0.43%), free (0.43%), bid (0.42%)
5	please (1.58%), trying (1.39%), hard (1.04%), really (0.96%), chance (0.93%), im (0.80%), give (0.78%),

²⁷ This is more than a sufficient number of iterations for each experiment to converge. In no case did an experiment’s log likelihood change by more than 0.4% between the 150th and 200th iteration.

know (0.72%), start (0.71%), little (0.68%), got (0.64%), someone (0.62%), name (0.61%), track (0.57%), things (0.56%), thanks (0.56%), right (0.55%), getting (0.54%), looking (0.53%), behind (0.51%), bad (0.50%)

6 prosper (2.28%), total (2.24%), gas (1.41%), rent (1.24%), per (1.21%), mo (1.02%), card (1.01%), cell (0.79%), balance (0.69%), left (0.56%), budget (0.55%), taxes (0.53%), auto (0.52%), bank (0.50%), electric (0.49%), account (0.48%), mortgage (0.45%), misc (0.45%)

7 medical (2.50%), surgery (1.04%), husband (0.89%), care (0.87%), due (0.86%), hospital (0.77%), mother (0.75%), son (0.70%), health (0.67%), family (0.63%), daughter (0.58%), cancer (0.57%), life (0.56%), wife (0.51%), take (0.51%), last (0.48%), behind (0.48%), since (0.45%), could (0.41%), ago (0.40%), disability (0.39%), father (0.38%)

8 business (8.70%), new (1.02%), sales (0.88%), store (0.79%), equipment (0.79%), purchase (0.71%), inventory (0.70%), expand (0.60%), used (0.60%), small (0.59%), start (0.56%), personal (0.50%), started (0.47%), capital (0.46%), well (0.45%), customers (0.44%), open (0.43%), cash (0.43%), office (0.42%), already (0.40%), service (0.39%), profit (0.38%), ebay (0.38%), advertising (0.36%), growing (0.36%), grow (0.35%), location (0.34%), increase (0.34%)

9 business (1.79%), marketing (0.57%), new (0.51%), website (0.41%), services (0.39%), web (0.37%), site (0.37%), people (0.35%), industry (0.34%), market (0.32%), well (0.32%), experience (0.31%), community (0.31%), many (0.30%), software (0.30%), project (0.30%), clients (0.30%), development (0.29%), professional (0.28%), service (0.27%), design (0.27%), funding (0.27%), plan (0.26%), training (0.26%), computer (0.26%), funds (0.24%), companies (0.24%), sales (0.24%), first (0.24%), local (0.23%), successful (0.23%), music (0.23%)

10 rent (3.48%), mortgage (3.37%), total (3.05%), budget (2.90%), using (0.93%), explain (0.88%), candidate (0.87%), included (0.32%), purpose (0.27%)

11 used (3.17%), candidate (3.10%), housing (2.92%), because… (1.11%), to… (1.10%), high (0.41%), never (0.37%), always (0.33%), card (0.29%), late (0.25%), interest (0.23%), steady (0.20%), history (0.19%)

12 housing (2.26%), trying (0.65%), track (0.63%), behind (0.61%), getting (0.48%), house (0.47%), due (0.43%), got (0.41%), little (0.40%), catch (0.38%)

13 used (3.79%), candidate (3.72%), housing (2.95%), to… (2.17%), because… (2.13%), because…i (0.38%), hard (0.34%), to…pay (0.15%), worker (0.13%), person (0.13%), honest (0.13%), always (0.12%), buy (0.11%), responsible (0.11%), repay (0.10%)

14 housing (3.17%), full (0.63%), wife (0.52%), employed (0.40%), stable (0.31%), steady (0.27%), purpose (0.24%), spouse (0.24%)

15 housing (2.95%), consolidate (0.92%), card (0.53%), start (0.40%), debts (0.39%), better (0.25%)

16 school (5.12%), college (3.04%), student (2.05%), degree (1.74%), education (1.04%), university (1.01%), tuition (0.99%), graduate (0.99%), full (0.79%), summer (0.61%), graduated (0.57%), classes (0.56%), program (0.53%), full-time (0.51%), finish (0.50%), semester (0.49%), go (0.47%), teacher (0.46%), books (0.45%), career (0.44%), teaching (0.40%), last (0.38%)

17 name (2.28%), deleted (1.72%), last (1.65%), truck (1.45%), vehicle (1.38%), new (1.30%), purchase (0.78%), buy (0.62%), live (0.48%), old (0.48%), 'm (0.47%), gas (0.47%), looking (0.46%), week (0.46%), miles (0.45%), transportation (0.44%), repair (0.41%), email (0.40%), drive (0.40%)

18 prosper (3.94%), total (1.44%), listing (1.32%), left (0.99%), promise (0.96%), see (0.92%), priority (0.77%), day (0.72%), top (0.70%), viewing (0.69%), made (0.63%), gas (0.63%), old (0.62%), every (0.55%), details (0.55%), rent (0.54%), life (0.53%)

19 card (1.82%), score (1.64%), debts (0.93%), consolidate (0.91%), improve (0.87%), high (0.83%), goal (0.79%), past (0.78%), interest (0.76%), future (0.74%), free (0.66%), rating (0.62%), used (0.52%), candidate (0.51%), start (0.50%), looking (0.46%), trying (0.45%), hard (0.44%), better (0.44%)

20 interest (6.45%), card (3.93%), high (3.88%), rate (3.74%), lower (1.29%), rates (1.14%), balance (0.99%), score (0.83%), late (0.77%), consolidate (0.75%), higher (0.73%), never (0.69%), prosper (0.60%), balances (0.59%), bank (0.54%), used (0.52%), low (0.51%)

21 wife (2.96%), per (1.70%), military (1.51%), husband (1.39%), security (1.15%), social (0.76%), retirement (0.74%), army (0.73%), disability (0.71%), family (0.69%), retired (0.67%), pays (0.62%), service (0.61%), receive (0.59%), navy (0.45%), check (0.44%), officer (0.44%), government (0.44%), married (0.44%)

22 past (1.11%), new (0.96%), last (0.93%), position (0.90%), wife (0.77%), due (0.75%), salary (0.70%), worked (0.69%), family (0.61%), since (0.57%), ago (0.57%), employed (0.54%), recently (0.49%), employment (0.44%), stable (0.41%), well (0.40%), several (0.39%), employer (0.38%), industry (0.37%)

23 payday (3.70%), behind (0.99%), interest (0.99%), cash (0.69%), every (0.67%), day (0.64%), got (0.63%), trying (0.60%), fees (0.60%), paycheck (0.55%), high (0.54%), due (0.54%), track (0.53%), catch (0.52%), n't (0.52%), getting (0.51%), could (0.51%), caught (0.50%), account (0.48%)

24	n't (1.22%), week (1.07%), husband (0.98%), wedding (0.96%), full (0.94%), extra (0.72%), every (0.72%), hours (0.64%), fiance (0.62%), rent (0.52%), pays (0.51%), go (0.50%), getting (0.50%)
25	explain (4.93%), candidate (3.18%), using (3.14%), housing (2.73%), always (0.10%), purpose (0.09%), debts (0.09%), consolidate (0.07%), consolidation (0.07%), none (0.07%), steady (0.06%), person (0.05%)
26	amount (0.92%), due (0.82%), funds (0.64%), however (0.61%), repay (0.43%), allow (0.40%), account (0.39%), request (0.36%), debts (0.35%), additional (0.35%), personal (0.33%), well (0.32%), provide (0.32%), cover (0.32%), plan (0.31%), obligations (0.31%), savings (0.31%), order (0.31%), repayment (0.29%), may (0.29%), fees (0.29%)
27	'm (1.63%), life (1.48%), know (1.24%), chance (1.18%), n't (1.13%), give (0.85%), past (0.83%), hard (0.81%), made (0.78%), people (0.76%), start (0.75%), person (0.69%), take (0.66%), someone (0.66%), 've (0.65%), please (0.64%), mistakes (0.64%), family (0.55%), better (0.55%), trying (0.53%), way (0.53%), really (0.51%)
28	house (3.06%), new (1.96%), repairs (0.84%), roof (0.57%), finish (0.55%), repair (0.51%), purchase (0.51%), water (0.51%), room (0.50%), done (0.47%), mortgage (0.46%), put (0.46%), needs (0.45%), kitchen (0.45%), purchased (0.45%), needed (0.44%), replace (0.44%), wife (0.42%), building (0.42%), complete (0.39%), old (0.36%), bought (0.36%), property (0.36%), improvements (0.36%), sell (0.35%)
29	n't (2.23%), 'm (1.23%), 've (0.95%), could (0.87%), got (0.75%), know (0.71%), going (0.66%), go (0.64%), even (0.62%), really (0.61%), much (0.60%), things (0.53%), never (0.50%), since (0.49%), way (0.49%), little (0.48%), right (0.48%), still (0.47%), life (0.46%), well (0.45%), ago (0.44%), everything (0.43%), started (0.41%)
30	bankruptcy (1.78%), report (1.74%), due (1.02%), since (0.97%), accounts (0.93%), ago (0.92%), score (0.91%), late (0.80%), past (0.76%), mortgage (0.67%), divorce (0.63%), file (0.62%), medical (0.61%), last (0.60%), filed (0.58%), husband (0.58%), house (0.55%), never (0.54%), account (0.54%), still (0.49%)

The final text model uses topics generated using word2vec, a text analysis method in which words are mapped to a vector in a high dimension semantic space. Mikolov et al. (2013) have shown that the resulting vectors can be used in arithmetic operations that highlight the semantic content of the words, and statements of analogical reasoning are possible. For example, relations are preserved, e.g. “biggest” – “big” + “small” = “smallest” and “Paris” – “France” + “Italy” = “Rome.”

As before, the loan application text is cleaned by removing punctuation and converting to lowercase. However, stopwords are not removed; the original text’s structure is maintained as closely as possible, since word2vec’s approach relies on words’ local context. The corpus used in Mikolov et al. (2013) contained 6 billion tokens, two orders of magnitude larger than the Prosper dataset used here (66 million tokens). As a result, the size of the vocabulary and the dimensions of the semantic space here are more modest; I use a vocabulary of the 5,000 most common words and,

though I experimented with 64 and 128 dimensions, chose 64 in order to reduce the number of inputs to the subsequent classifier. To illustrate the results, Figure 14 shows a 2-dimensional projection of these 64 vectors created using t-SNE. Though much information is lost and therefore the graphical representation is merely impressionistic, some intuitively related words do appear to be close to one another, for example, “income,” “job,” “employment,” “position” and “salary” as do some grammatical terms, like “can’t,” “don’t,” “may,” “will” and “should.”

Since each word is mapped to a vector and each loan listing is a body of text that can be thought of as a collection of words, I sum the vectors for all of the words in each listing to produce a single vector for each listing. In this way, each listing is represented in 64 numeric features, one for each dimension.

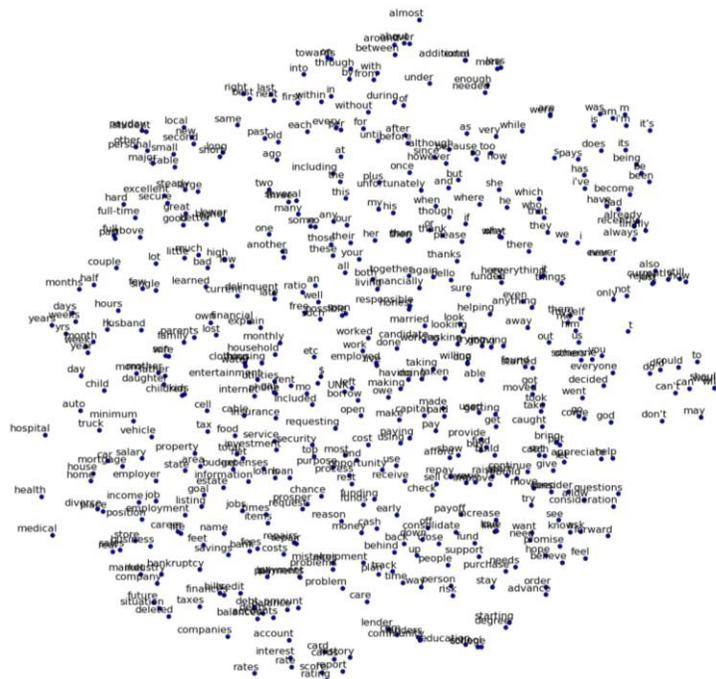


Figure 14. A 2-D projection of the 64 dimensions produced by word2vec.

Results

As described above, the first set of models includes the primary economic indicators, including credit grade, loan amount, and debt to income ratio. The next two sets of models include models with binary indicators for the presence of a photo and group membership. Because the effects of the economic indicators are consistent across these models, the following discussion includes both the economic inputs as well as those for photos and group membership. Table 7 shows the results of the logistic regression models for whether a listing is funded and whether the resulting loan is charged off, as well as the OLS model for borrower interest rate:

Table 7. Regression model results, including economic inputs, photo presence and group membership.

<u>Input</u>	<u>Listing Funded</u>	<u>Borrower Rate</u>	<u>Loan Charged Off</u>
Constant	0.239 *** (0.057)	12.467 *** (0.212)	-1.781 *** (0.100)
Amount Requested (\$1,000's)	-0.126 *** (0.002)	0.252 *** (0.006)	0.080 *** (0.003)
DTI in Excess of 100%	0.243 *** (0.065)	-1.446 *** (0.271)	-0.449 *** (0.123)
DTI Unknown	-1.882 *** (0.037)	3.555 *** (0.149)	0.665 *** (0.070)
Debt to Income Ratio (DTI) Percent	-0.021 *** (0.001)	0.048 *** (0.002)	0.010 *** (0.001)
Is Homeowner	0.000 *** (0.016)	0.485 *** (0.061)	0.394 *** (0.029)
Credit Grade AA	0.860 *** (0.037)	-5.569 *** (0.110)	-1.118 *** (0.060)
Credit Grade A	0.409 *** (0.034)	-2.933 *** (0.110)	-0.487 *** (0.054)
Credit Grade B (omitted)	---	---	---
Credit Grade C	-0.825 *** (0.027)	3.477 *** (0.097)	0.424 *** (0.045)
Credit Grade D	-1.666 *** (0.028)	7.280 *** (0.101)	0.758 *** (0.047)
Credit Grade E	-2.770 *** (0.031)	12.518 *** (0.117)	1.324 *** (0.053)
Credit Grade HR	-3.944 *** (0.031)	13.311 *** (0.120)	1.981 *** (0.056)
Credit Grade NC	-2.469 *** (0.104)	9.950 *** (0.420)	2.345 *** (0.195)
Duration of Listing: 3 days	---	---	---
Duration of Listing: 5 days	0.208 *** (0.043)	-0.328 * (0.164)	0.065 (0.076)

Duration of Listing: 7 days	-0.077 *	-0.269 *	-0.115 *
	(-0.032)	(0.118)	(0.055)
Duration of Listing: 10 days	0.281 ***	-0.146 *	0.006
	(0.019)	(0.071)	(0.033)
Duration of Listing: 14 days	0.181	0.875	-0.131
	(0.140)	(0.467)	(0.228)
Borrower is Group Member	0.432 ***	-0.634 ***	-0.019
	(0.019)	(0.069)	(0.032)
Listing Includes Photo	0.472 ***	-0.551 ***	-0.124 ***
	(0.016)	(0.063)	(0.029)
Length of Text (words)	0.003 ***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Quarter: 0 th	---	---	---
Quarter: 1 st	0.572 ***	-0.087	-0.062
	(0.050)	(0.187)	(0.087)
Quarter: 2 nd	0.465 ***	-0.788 ***	-0.030
	(0.048)	(0.181)	(0.084)
Quarter: 3 rd	0.707 ***	-1.692 ***	-0.075
	(0.047)	(0.174)	(0.081)
Quarter: 4 th	0.358 ***	-1.043 ***	-0.049
	(0.047)	(0.174)	(0.081)
Quarter: 5 th	0.065	-0.249	0.006
	(0.047)	(0.177)	(0.083)
Quarter: 6 th	-0.100 *	-0.508 **	-0.023
	(0.048)	(0.181)	(0.085)
Quarter: 7 th	-0.215 ***	0.522 **	-0.128
	(0.047)	(0.178)	(0.084)
Quarter: 8 th	0.098 *	0.515 **	-0.018
	(0.046)	(0.173)	(0.081)
Quarter: 9 th	0.205 ***	2.414 ***	-0.139
	(0.047)	(0.177)	(0.083)
Quarter: 10 th	-0.049	3.287 ***	-0.141
	(0.055)	(0.209)	(0.099)
Log Likelihood	-60,894	---	-17,226
R ²	---	0.59	---
N	220,125	28,950	28,950

Standard errors in parentheses.

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

The likelihood of a listing being successfully funded as a loan varies predictably, based on economic criteria. Each extra \$1,000 of principal requested decreases the likelihood of funding by about 12%. Each percentage point increase in the borrower's debt to income ratio decreases the likelihood of funding by about 2%, those with unknown debt loads having about the same funding likelihood as someone with a 41% debt to income ratio. Funding likelihood decreases with credit grade;

compared to a credit rating of B, people with AA and A credit ratings are 136% and 51% more likely to be funded, and people with C, D, E and HR credit grades are 56%, 81%, 94% and 98% less likely to be funded, respectively.

Economic indicators have likewise similar effects on interest rate, conditioned on loans successfully being funded. Each extra \$1,000 of principal is associated with an interest rate that is 0.25% (in absolute terms) higher. Each percentage point increase in the debt to income ratio is associated with an increased interest rate of 4.8 bps, but the interest rate penalty for having unknown debt is over 3.5%. Higher interest rates paid as credit grade decreases; compared to a rating of B, borrowers with AA and A credit ratings pay 5.6% and 3.0% less, respectively, while people with C, D, E and HR credit grades pay from 3.5% more to 13.3% more. Interestingly, homeownership is associated with a nearly 0.5% higher interest rate, though it had no meaningful effect on whether a loan was funded.

It is arguably reasonable that borrowers might experience the outcomes described above, as those characteristics are associated with loan charge-offs in the expected ways. Each additional \$1,000 of principal increases a loan's likelihood of charge-off by 8.3%, and an unknown debt to income ratio is associated with a nearly doubling of the likelihood of charge-off. Compared to loans with borrowers with credit grade B, grade AA and A borrowers are associated with a 67% and 39% lower likelihood of charge-off, while for borrowers with grades C through HR, charge-off rates range from 53% higher to a massive 625% higher.

The higher interest rate charged for home ownership might be explained by the observation that home ownership is associated with a 48% increase in the likelihood of

charge off; when borrowers are short on funds, they most likely choose to pay their mortgages before their unsecured loans.

Considering the effects that group membership have on trust and identity and driving bidders to a listing, it is not unexpected that being a group member is beneficial for the borrower. Group membership is associated with a 54% increase in the likelihood of being funded, and with a 0.63% decrease in interest rate. However, group effects may make lenders overconfident in borrowers' creditworthiness or commitment, as group membership is not associated with a decreased likelihood of charging off.

Tree-Based Models

The above models are traditional regression models that might be familiar to any social scientist, and there are real problems associated with the use of the p value as a measure of significance of effect. In particular, notional significance is impacted by the size of the data used to fit the model, since the standard error is a function of the observation count, the t statistic is as well. As a result, sufficiently large datasets like the Prosper dataset used here, will generate results that are statistically "significant" even if their practical significance is limited. Second, these models are trained on the full dataset, so it is not clear whether the effects observed would generalize to additional data; in other words, the model may overfit to the data given to it, and an observer might not be confident in how it fits the outside world.

To address these challenges, in addition to the models described above, I fit each model again, but using AdaBoost (Freund and Schapire 1997) with decision trees as the constituent weak learners. Through experimentation, I found that increasing the

depth of the decision trees improved overall learner performance, and that taken together, this approach outperformed logistic regression by having superior recall. All models were learned with a consistent 85/15% train/test split. Model performance on the 15% holdout set is shown in Table 8.

Table 8. Performance of models learned using adaptive boosting

<u>Evaluation Method</u>	<u>Listing Funded</u>		<u>Borrower Rate</u>	<u>Loan Charged Off</u>	
AUC	0.60			0.56	
Precision	0.48			0.47	
Recall	0.23			0.43	
Confusion Matrix	Predicted			Predicted	
		No Yes			No Yes
	Actua	No 27,803 1,068		Actua	No 1,943 826
		Yes 3,367 995			Yes 972 722
R ²			0.57		
Mean absolute error (MAE)			3.26		
Mean abs. percent error (MAPE)			19%		

The classification models’ results indicate, generally, low classification accuracy, as measured using the AUC, or area under the ROC curve. An intuitive interpretation of the AUC is, if all examples were arranged in order of the prediction, what fraction of pairs of examples would be correctly ordered? A random model would have an AUC of 0.5, while a perfect model would have an AUC of 1.0. Accordingly, AUCs of 0.60 and 0.56 as shown in Table 8 indicate poor ability to correctly classify those listings that would be funded, and those loans that would charge off.

Because decision trees are initialized with a random state, and because learner performance is somewhat dependent on the specifics of the train/test split, it is worthwhile to examine model performance when the model is trained multiple times, and on multiple train/test splits. Running the loan completion model 20 times with a

different random split yields AUC values ranging from 0.59 to 0.61 ($M = 0.60$, $sd = 0.005$), with recall ranging from 0.45 to 0.50 and precision from 0.21 to 0.25. The interest rate models' R^2 ranges from 0.50 to 0.56, with mean absolute error ranging from 3.3% to 3.5%. Finally, the charge-off model's AUC ranges from 0.55 to 0.58, with precision ranging from 0.43 to 0.49 and recall from 0.33 to 0.44. The variations in these evaluation metrics that are due entirely to the effects of random sample selection help us contextualize the variations observed between other pairs of models when the intent is to use those differences to understand the substantive effects of the inputs.

In the regression models described earlier, the impact of each input is interpreted by considering its t statistic. I now consider two other approaches to understanding an input's importance.

First, I build each model with each input (or family of inputs, e.g. all duration dummies taken together) either used as the sole predictor or excluded from the otherwise full model specification. This one-factor-at-a-time approach is useful for identifying how much information an input contributes on its own (i.e. the simple, bivariate relationship), and for understanding the unique information it contributes; if excluding an input from the model does not meaningfully decrease the model's accuracy, then one can conclude that that input does not contribute any unique information.²⁸

As shown in Table 9, credit grade is overwhelmingly the most impactful

²⁸ Worse, if a model's accuracy improves by excluding an input, then the model may

Table 9. Degradation in model performance relative to full model, when individual inputs are omitted

<u>Input (family) Omitted</u>	<u>Listing Funded</u>	<u>Borrower Rate</u>	<u>Loan Charged Off</u>
Amount Requested (\$1,000's)	1%	21%	2%
Credit Grade	12%	96%	6%
Debt to Income Ratio	1%	13%	0%
Duration of Listing	0%	2%	0%
Borrower is a Group Member	0%	1%	0%
Is Homeowner	0%	1%	0%
Listing Includes Photo	0%	2%	1%
Length of Text (words)	-4%	8%	0%
Quarter (0 – 10)	-1%	10%	3%

The values reported for the funding model and charge-off model are $1 - \frac{AUC_{input}}{AUC_{full}}$, or the relative change (decrease) in model accuracy. For the borrower rate model, the values are $\frac{MAPE_{input}}{MAPE_{full}} - 1$, or the percentage increase in error. This way, for all models, larger numbers indicate worse performance and 0 indicates no change compared to the full model.

family of inputs across all three targets, and the only family of inputs with meaningful predictive power for the model that predicts whether or not a listing will be funded. As we see, though the inputs for duration, listing and quarter, for example, are statistically significant in the regression models, omitting them from the tree-based model has no discernible impact on the models' performance, suggesting that they are not in fact substantively important drivers of outcomes.

A standout here is quarter, which does not help predict whether a listing is funded or a loan is charged off, but does appear to contribute to the ability to predict interest rate. If lender's behavior change over time consists of changes to the rates they charge borrowers rather than who they lend to, then this is supportive of the hypothesis that lenders price discriminate, rather than ostracize (Chen et al. 2008).

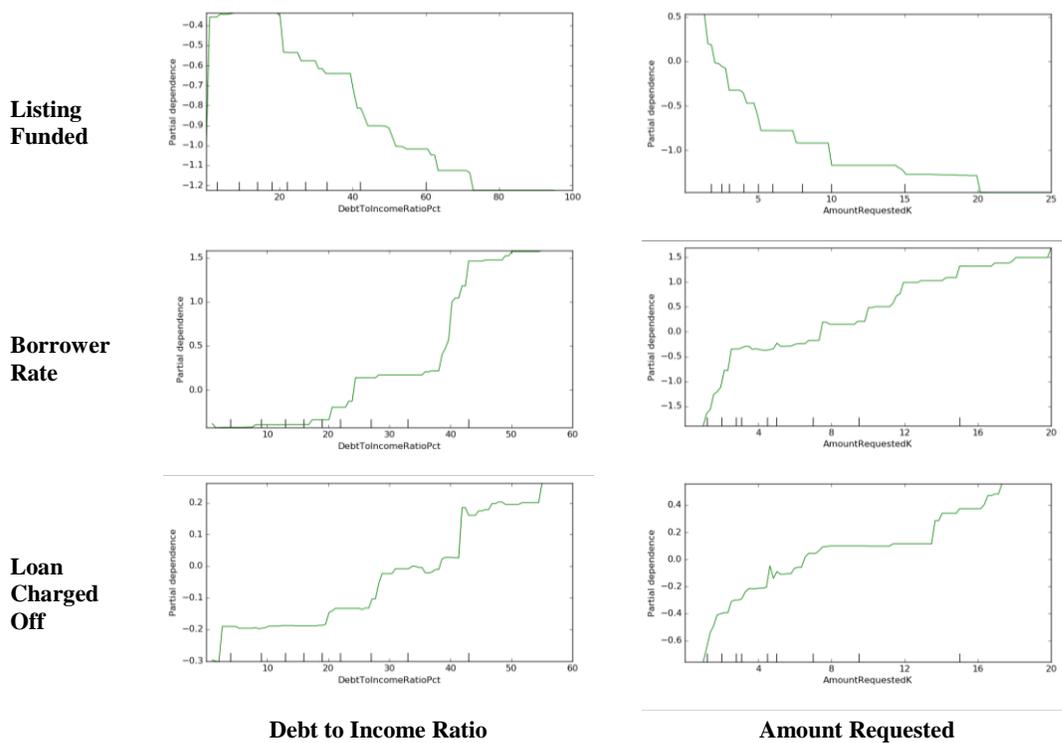


Figure 15. Partial dependence plots of debt-to-income ratio and loan amount requested.

Second, I generated partial dependence plots (Hastie et al. 2009) for each input. The partial dependence plot describes the effect of each variable on the target after averaging the effects of all the other variables, over the range of the input. In contrast, a coefficient in a regression model describes the effect of each variable, all others held constant – an assumption which may generate unrealistic predictions when considering combinations of inputs that lie outside the space of observed inputs. A partial dependence plot also provides a finer-grained analysis than a regression coefficient, which, interpreted as a slope, indicates the size and direction of any effect. For example, consider the effects of debt to income ratio and loan amount on funding, interest rate, and charge off (Figure 15). As expected, listing funding decreases with debt load and interest rate and charge-off likelihood increase, but debt has little effect

on interest rate between about 25% and 40%, impacting the price borrowers pay only when outside that range.

Within-Credit Grade Models

One of the reasons the models above may perform the way they do, is that the effects of various behaviors are not consistent across credit grades. Intuitively, a lender might consider a high-credit grade borrower capable of handling an increased debt load, so might not penalize an AA or A grade borrower quite so heavily for having a high debt to income ratio as they might a D or HR grade borrower. To test this, I re-trained each of the models of interest (listing funded, borrower rate, and loan charge off) once for each credit grade, using in each training set only those examples in which the borrower’s credit grade was in the focal category. Another way of approaching this might have been to include interaction terms, interacting each input of interest with credit grade, but with seven credit grades, the number of inputs would make interpretation cumbersome.

Learning models separately for credit grades reveals that the models learn more effectively – using the same set of inputs – for the better credit grades. Table 10

Table 10. Model performance by credit grade.

Credit Grade	Listing Funded				Borrower Rate				Loan Charged Off			
	<i>N</i>	<i>AUC</i>	<i>Prec.</i>	<i>Rec.</i>	<i>N</i>	<i>R²</i>	<i>MAE</i>	<i>MAPE</i>	<i>N</i>	<i>AUC</i>	<i>Prec.</i>	<i>Rec.</i>
AA	1,063	0.65	0.64	0.69	517	0.47	1.40	13%	517	0.56	0.31	0.27
A	1,313	0.65	0.60	0.54	500	0.49	2.03	15%	500	0.54	0.33	0.28
B	2,008	0.63	0.56	0.44	659	0.19	2.58	16%	659	0.55	0.38	0.41
C	3,542	0.63	0.49	0.39	857	0.17	3.68	21%	857	0.52	0.40	0.38
D	4,975	0.56	0.37	0.18	772	-0.01	4.12	20%	772	0.53	0.45	0.42
E	5,960	0.54	0.28	0.11	487	0.01	4.13	18%	487	0.49	0.47	0.47
HR	14,576	0.53	0.25	0.06	516	0.09	4.47	25%	516	0.50	0.60	0.64

shows that AUC for both classification models decreases with credit grade, and the mean absolute percentage error (MAPE) of the rate prediction model increases. To explain why this is the case, consider that unpredictability varies with credit grade.²⁹ The charge-off models indicate that whether or not a loan will be charged off becomes harder to predict as credit score decreases – though the models’ AUCs indicate that it is barely, if at all, better than random in all cases. If that is so, a reasonable lender might lean more heavily on non-economic criteria to make their decisions. The results shown in Table 11 support this somewhat; the importance of loan amount, debt ratio are greater for models for the higher credit grades for predicting both funding and interest rate. However, group membership’s impact is contrary to expected, being higher for the middle credit grades for funding and for the higher credit grades for interest rate -- if the prediction held, then group membership would have been more impactful for the lower credit grades – the percentages being small relative to those observed for amount and debt, the differential effects of group membership may be considered uncertain.

Text Analysis Models

I next examine a series of models that include all of the inputs described earlier, as well as the inputs created by applying the various text analysis methods to the listing descriptions. If non-economic information has an impact, then including

²⁹ It is also important to consider that the difference may be artifactual. Model accuracy is driven in part by the number of training examples. However, we see that observation count mostly increases as credit grade decreases. Another possibility to be considered for the classification models is class imbalance. Though the imbalance is sometimes large for loan funding (only 4% of HR listings are funded), for charge-offs, the imbalance is not substantial; AA grade has the lowest rate of charge-off at 19%.

Table 11. Within-credit grade model performance relative to full model, when inputs are omitted

Model	Input	Credit Grade						
		AA	A	B	C	D	E	HR
Listing Funded	Amount Requested (\$1,000's)	8%	9%	12%	10%	4%	4%	1%
	Debt to Income Ratio	6%	10%	7%	6%	4%	1%	-1%
	Duration of Listing	-1%	3%	0%	2%	1%	2%	2%
	Borrower is a Group Member	0%	0%	2%	3%	0%	-1%	0%
	Is Homeowner	-1%	2%	-1%	3%	1%	1%	0%
	Listing Includes Photo	-1%	-1%	2%	0%	0%	2%	-1%
	Length of Text (words)	-2%	1%	-1%	1%	0%	0%	0%
	Quarter (0 – 10)	-1%	4%	2%	3%	0%	3%	0%
Borrower Rate	Amount Requested (\$1,000's)	70%	56%	26%	23%	13%	10%	1%
	Debt to Income Ratio	32%	29%	15%	14%	3%	-3%	1%
	Duration of Listing	-1%	5%	1%	2%	2%	-3%	1%
	Borrower is a Group Member	3%	6%	2%	0%	0%	0%	0%
	Is Homeowner	3%	4%	4%	3%	-4%	3%	-4%
	Listing Includes Photo	5%	6%	-1%	1%	1%	2%	3%
	Length of Text (words)	3%	11%	5%	13%	6%	1%	5%
	Quarter (0 – 10)	14%	12%	9%	11%	12%	12%	8%
Loan Charged Off	Amount Requested (\$1,000's)	9%	11%	2%	6%	-1%	-4%	0%
	Debt to Income Ratio	-2%	1%	0%	0%	8%	-4%	-4%
	Duration of Listing	0%	0%	5%	1%	1%	-5%	-2%
	Borrower is a Group Member	-3%	-2%	-3%	-2%	-3%	1%	-3%
	Is Homeowner	3%	1%	-1%	-4%	4%	-2%	0%
	Listing Includes Photo	-11%	1%	0%	3%	-4%	-4%	1%
	Length of Text (words)	0%	-2%	-3%	1%	5%	-8%	0%
	Quarter (0 – 10)	-1%	5%	-1%	-2%	5%	-7%	0%

Values represent percentage decrease in model performance See Table 9 for further information.

those inputs in the models should result in an improved ability to predict the outcomes.

Table 12 shows that loan charge-offs appear to be inconsistently impacted, suggesting that the changes are due to noise rather than a substantive effect; worse, listing funding is consistently negatively impacted. An investigation of the precision and recall of these models reveals that precision does not change significantly from the model with no text analysis, but including the text analysis inputs causes recall to

Table 12. Absolute and relative model performance when text analysis inputs are included.

Method	Listing Funded		Borrower Rate			Loan Charged Off
	AUC	MAE	MAPE	RMSE	AUC	
(None)	0.60	3.26	19.0%	4.88	0.56	
LIWC	0.53 (-10.9%)	3.20 (1.9%)	18.7% (1.8%)	4.69 (3.9%)	0.57 (1.1%)	
ANew	0.55 (-8.5%)	3.22 (1.2%)	18.8% (1.2%)	4.77 (2.2%)	0.55 (-1.7%)	
LDA	0.56 (-5.6%)	3.18 (2.4%)	18.5% (2.6%)	4.66 (4.5%)	0.55 (-2.7%)	
Word2vec	0.52 (-12.6%)	3.21 (1.7%)	18.7% (1.5%)	4.66 (4.5%)	0.56 (0.1%)	
Combined	0.58 (-2.1%)	3.23 (0.9%)	18.8% (0.8%)	4.69 (3.9%)	0.57 (1.0%)	

Table 13. Absolute and relative model performance for borrower rate prediction, by credit grade (LDA model scores only).

Credit Grade	MAE		MAPE		RMSE	
	Baseline	With LDA	Baseline	With LDA	Baseline	With LDA
AA	1.40	1.34 (3.7%)	13.0%	12.7% (2.4%)	2.38	2.22 (6.9%)
A	2.03	2.02 (0.6%)	15.0%	14.7% (2.1%)	3.18	3.21 (-0.9%)
B	2.58	2.42 (6.0%)	16.4%	15.2% (7.8%)	3.78	3.60 (4.7%)
C	3.68	3.57 (2.9%)	21.0%	20.4% (3.2%)	5.16	4.97 (3.6%)
D	4.12	3.99 (3.1%)	20.4%	19.6% (4.0%)	5.80	5.43 (6.3%)
E	4.13	3.85 (6.8%)	18.5%	16.6% (10.2%)	5.50	4.89 (11.1%)
HR	4.47	4.41 (1.3%)	25.2%	25.2% (0.0%)	6.19	5.98 (3.4%)

Percentage improvement over model without text analysis is shown in parentheses.

decrease sharply, from 0.23, to values ranging from 0.05 to 0.14.

Only the borrower rate model is consistently improved by including text analysis. Regardless of the error metric considered (MAE, RMSE, MAPE), Latent Dirichlet Allocation (LDA) appears to generate the greatest increase in model performance, though all methods are associated with some model performance increase. Interestingly, however, a “combined” model that included all of the inputs generated by all of the text analysis methods performed less well than each method individually.³⁰ That the interest rate is generally better predicted with text analysis than without suggests that lenders are indeed attuned to the non-economic information borrowers are sharing, but are using this information to select the interest rate to charge them, rather than to select who to bid on.

³⁰ With one exception: the RMSE for the combined model is better than that of the model built using the

Selected examples are shown in Figure 16. Rhetorically, we see that begging is less effective than budgeting; the former – using terms like “please” and “thanks”^{31,32} and “needing a chance,” “getting back on track” and seeking a “fresh start” – is associated with higher interest rates, while the latter – using terms like “gas”, “rent”, “per mo[nth]”, “balance” and “budget” – is associated with lower interest rates.

Even net of the effect of the debt associated with them, certain kinds of personal financial misfortune are associated with paying higher interest rates. Debt resulting from a payday lender is associated with a higher interest rate, as is personal bankruptcy. However, perhaps seeming like comparatively responsible or savvy choice, consolidating high interest debt into a single, lower-interest loan is associated with a lower interest rate. Likewise, educational matters, perhaps suggesting a greater level of responsibility, are associated with lower interest rates.

As described above, if the impact of economic criteria on lending decisions decreases with credit grade, then non-economic criteria like the text-based inputs might be hypothesized to take on greater importance at the lower credit grades. To examine this, I break down the effects shown in Table 12 by credit grade; this is shown in Table 13, which shows, for borrower rate prediction, the absolute and relative model performance, compared to the model with no text analysis inputs (only

ANEW inputs.

³¹ Politeness in general may be expected to lead to *lower* interest rates rather than higher interest rates. Further, if mere politeness were intended, then the words’ importance to this topic might be lower. Instead, it is arguable that excessive politeness is what is on display here.

³² Topic 27 appears similar to 5 in content and has a similar shape.

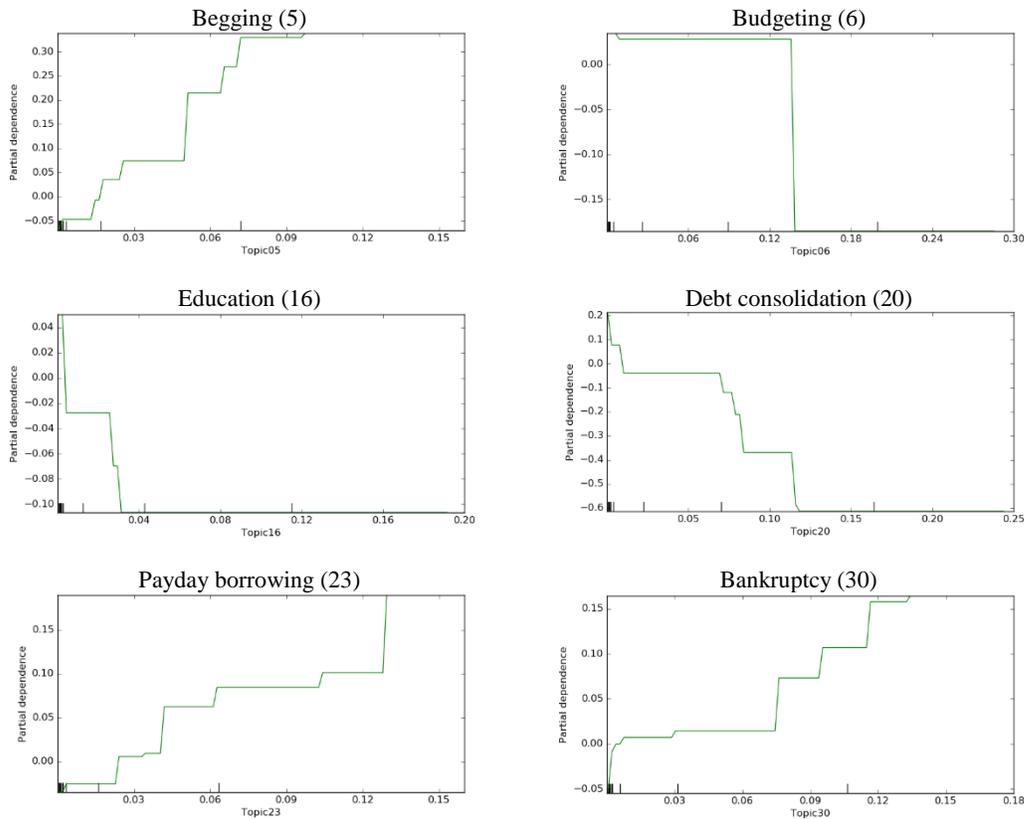
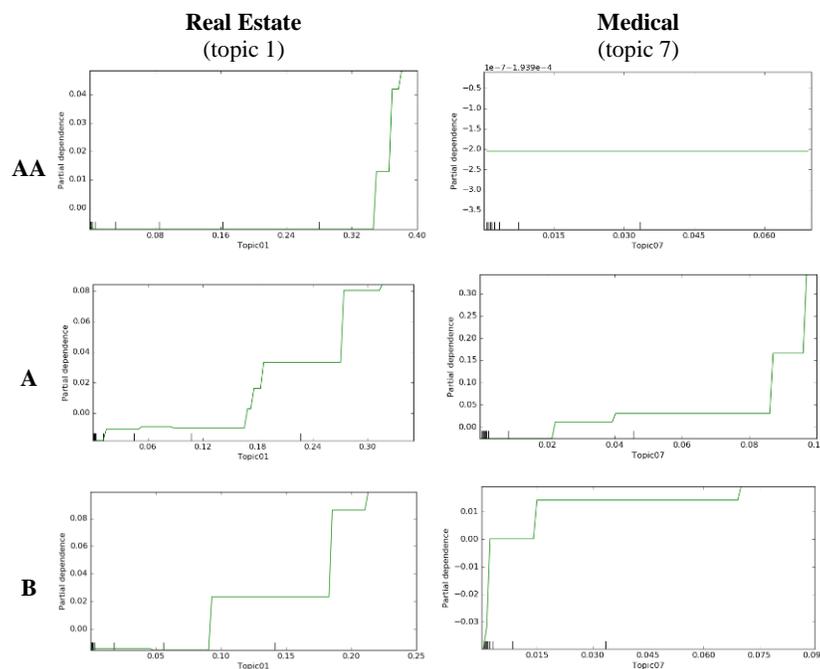


Figure 16. Partial dependence plots showing the impact of selected LDA-derived topics on borrower rate.

the results for LDA are shown, but the pattern for the other error metrics is similar). As in other cases, error mostly increases with credit grade, and as expected text analysis improves prediction in every case. However, contrary to expectations, neither the absolute nor relative improvement in any of the error metrics consistently increases as credit grade decreases, indicating that text content may not play a disproportionately increasing role as credit grade decreases, but merely a consistently positive role to varying extents.

It is worthwhile at this point to return to a hypothesis from earlier: that the effects of some topics might not be consistent across credit grades. Some borrowing purposes might be more impactful for high credit grades than low ones, or vice-versa.

For example, some of the life circumstances borrowers describe might be seen as insurmountable for some, but inconsequential for others, and the goals and reasons for borrowing may seem credible when expressed by some borrowers, but fanciful by others. Figure 17 suggests such a trend; partial dependence plots are shown for two topics, one real estate-related and one medical-related (see Table 6). The real estate topic has comparatively greater impact for the higher credit grades (AA, A, B) than the lower credit grades.³³ In contrast, medical topics impact credit grades C, D and E more than the higher credit grades (though impact on A spikes only at an extremely high level of topicality).



³³ For reference, a range on the y-axis of 0.1 indicates about an order of magnitude smaller impact than inputs like loan amount or debt level.

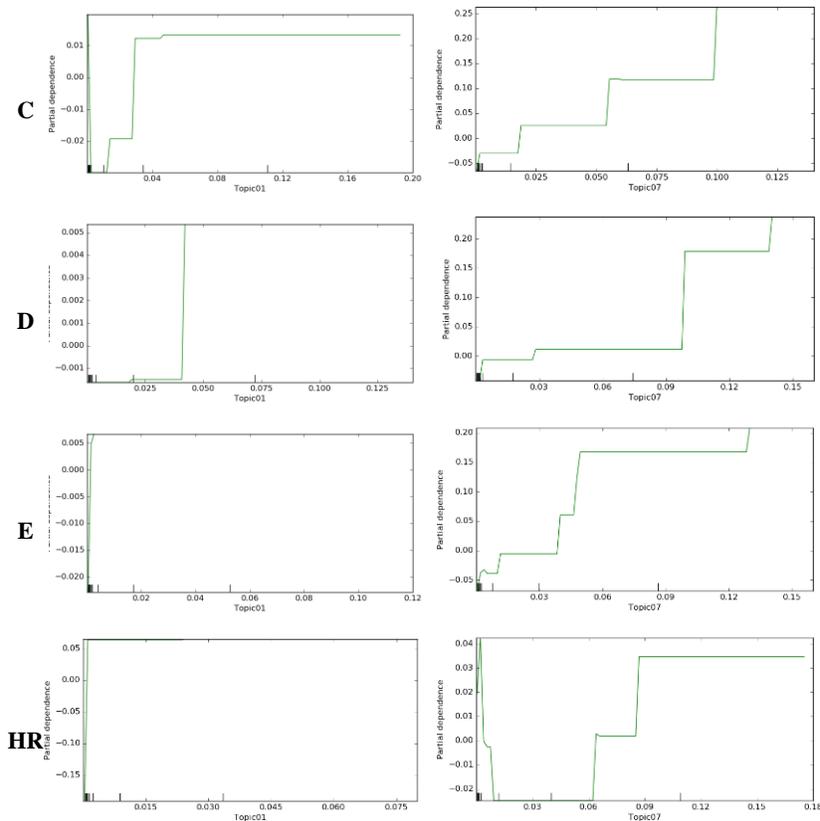


Figure 17. Partial dependence plots showing the impact of selected LDA-derived topics on borrower rate, broken down by credit grade.

Discussion

That economics dominates lending decisions in peer-to-peer microlending as it does in traditional financial services is neither surprising nor unexpected. Who was funded was largely determined by credit grade, debt level, and loan amount, and loan outcomes were not predictable beyond the expected association between credit grade and charge-off, who was funded and what interest rate they paid. Once borrowers were funded, however, there is support for the text content the borrowers wrote having an impact on what interest rate they were ultimately charged. In order for a borrower to receive a lower interest rate, either lenders must bid lower, or they must set their

reserve prices lower, and competition (i.e. greater lender interest) must drive the resulting interest rate down through the auction mechanism. That the effects were visible in the selection of interest rate rather than in who is funded supports Chen et al.'s (2008) finding that lenders use price discrimination when participating in the market rather than ostracizing riskier investments completely.

At the outset, I described some of the relationships between morality and debt, including the just-world theory that underpins the Weberian interpretation of the Protestant approach to capitalism, boiling down to a simplified view that people are responsible for, and deserve, their outcomes. This view contrasts with an understanding of the structural conditions around debt and poverty, recognizing that beyond consumerism, various misfortunes and macroeconomic conditions conspire to make it expensive to be poor. Using a variety of text analysis methods, I showed that people using words that indicate conventionally “good” choices like budgeting, seeking education and reasonable debt management paid lower interest rates than people whose prose indicated conventionally poor or irresponsible choices, like declaring bankruptcy or using payday lenders.³⁴ Further, some of these topics’ effects varied with the credit score of the borrower, some topics being deemed more credible or impactful at different credit score levels.

The value that text analysis brings to the social and behavioral sciences is as a kind of efficient, systematized and automated qualitative coding. Text analysis

³⁴ Note that these are merely popular views, not necessarily correct ones; Servon (2017) points to many reasonable factors that would drive consumers to payday lenders, including clearer fee structures and immediate availability of funds, which are not true of mainstream banks.

methods have long been used to derive structure from text, but typically has been accomplished through the careful reading of texts, the creation of themes and categories, and the reconciling of those themes and categories as the entire corpus is read and considered (Glaser and Strauss 1967; McFarland et al. 2016). Computational methods that extract topics and themes from text do this with a great degree of precision, but this precision should not be confused with accuracy. Judging the accuracy of output of text analysis requires, as I describe in Chapter 1, establishing *verstehen*, of treating online sites like ethnographic sites, and understanding the behavior and the larger social and cultural context of that behavior.

Relatedly, I presented two sets of models, first a traditional suite of regression models, but recognizing that the significance of these models is affected by the size of the dataset, I created a second set of models in which the impact of variables in the model was evaluated in part by considering how that variable contributed to the model's ability to better predict on a held out dataset. Using a holdout dataset is not yet a common practice in the social sciences, but ought to be, as it helps us understand how well a model generalizes, because we see not how much variation in the source data the model explains, but rather how much variation it explains in *other* data. By taking multiple approaches and seeing how those approaches' results agree and conflict, it is possible to achieve via triangulation a clearer understanding of what we know, and what we do not know.

Three factors potentially blunted the findings presented here, all of which are driven by features or mechanisms of the Prosper auction system.

First, borrowers had the opportunity to complete the auction as soon as

sufficient bids were received, rather than let the auction run the full duration. This had the effect of getting them the loan a few days faster, but cut off any competition before their interest rate was driven down to what the market might actually bear. That is, borrowers paid more than they needed to, and it is not knowable how much lower their interest rates might have gone. 26% of loans employed this early-closing feature.

Second, and relatedly, in order to protect lenders' information, the dataset does not include the minimum that a lender would have accepted (unless they were outbid), only their winning bid. If an auction closed at 11%, it is unknowable that some lenders would have been willing to accept 10% or 9%, for example.

Third, and most challenging, an unknown fraction of lenders used Prosper's auto-investment feature, which allowed lenders to set criteria for investment and made bids on their behalf. For example, a lender could invest up to \$50 in loans of grade B where the debt level is under 20% and the interest rate greater than 9.5%. In this case, the lender could bid on a large number of loans, but never see the text component of the listing, making it impossible for the non-economic information the borrower provided to have any impact on that lender.

These factors have something in common: they automate and routinize the lending process, taking the personal and social dimensions out of the process. If a lender can set up rules to automate their bidding, including who to bid on, how much to bid, and what reserve prices to set, then they can participate in many more loans.

A potentially interesting extension is suggested by asking, could an investor have traded profitably on the model improvement provided by text analysis? The number of blogs in the 2006-2008 period that traded tips, information and investment

strategies for lenders suggests this was indeed a pertinent question for the time. Though investors generally demand greater return for greater risk (Derman 2013), Zeckhauser (2006) points out that investors seek mispriced risk; if the text-based model predicted a loan was less risky than the economic model suggested, an investor could in theory buy that loan and receive more for his money than he might otherwise. It could be possible to run the predictive model in simulation format in two flavors, with and without the benefits of text analysis, perhaps simulating an investment in a random sample of most promising loans each day; the value of the text-derived information would be characterized by examining the distribution of the incremental increase in returns over multiple simulations. There are some practical challenges to doing this; all the models in this chapter were trained and tested on randomly selected holdout datasets, which included the final outcome of each loan as ground truth. A functioning trading model would have to be learned using a time-based holdout set, and with much smaller time horizons (one could not train on the 2006-2007 cohort and trade on 2008, for example, if one needed to wait until the training loans' amortization periods ended); however, as Figure 13 indicates, loan status at 3 or 6 months may be a poor indicator of loans' final status.

BIBLIOGRAPHY

- Adamic, Lada A. and Natalie Glance. 2005. "The Political Blogosphere and the 2004 U.S. Election: Divided They Blog." Pp. 36–43 in *Proceedings of the 3rd international workshop on Link discovery*.
- Adamic, Lada and Eytan Adar. 2005. "How to Search a Social Network." *Social Networks* 27(3):187–203.
- Anderson, Carolyn J., Stanley Wasserman, and Bradley Crouch. 1999. "A P{*} Primer: Logit Models for Social Networks." *Social Networks* 21(1):37–66.
- Anderson, Chris. 2008. "The End of Theory: The Data Deluge Makes the Scientific Method Obsolete." *Wired*, June. Retrieved (<https://www.wired.com/2008/06/pb-theory/>).
- Anon. 2008. "SEC News Digest." (2008–227). Retrieved (<https://www.sec.gov/news/digest/2008/dig112408.htm>).
- Anon. 2009. *How Undergraduate Students Use Credit Cards: Sallie Mae's National Study of Usage Rates and Trends 2009*.
- Anon. 2014. "Peer-to-Peer Lending: Ready to Grow, Despite a Few Red Flags." *Knowledge@Wharton*. Retrieved (<http://knowledge.wharton.upenn.edu/article/peer-peer-lending-ready-grow-despite-red-flags/>).
- Anon. 2015. "Review: Top Prosper Blogs." 1–7. Retrieved (http://prosperlending.blogspot.com/2007/06/review-top-prosper-blogs_28.html).
- Anthony, Denise, Sean W. Smith, and Tim Williamson. 2009. "Reputation and Reliability in Collective Goods: The Case of the Online Encyclopedia Wikipedia." *Rationality and Society* 21(3):283–306.
- Aral, Sinan, Lev Muchnik, and Arun Sundararajan. 2009. "Distinguishing Influence-Based Contagion from Homophily-Driven Diffusion in Dynamic Network." *Proceedings of the National Academy of Sciences* 106:21544–49.
- Ashby, F. G., V. V. Valentin, and U. Turken. 2002. "The Effects of Positive Affect and Arousal on Working Memory and Executive Attention: Neurobiology and Computational Models." Pp. 245–87 in *Emotional Cognition: From Brain to Behaviour*, edited by S. Moore and M. Oaksford. Amsterdam: John Benjamins.
- Ayres, Ian, Mahzarin Banaji, and Christine Jolls. 2015. "Race Effects on eBay." *RAND Journal of Economics* 46(4):891–917.
- Backstrom, Lars, Cynthia Dwork, and Jon Kleinberg. 2007. "Wherefore Art Thou R3579X? Anonymized Social Networks, Hidden Patterns, and Structural Steganography." in *WWW 2007*.
- Backstrom, Lars, Dan Huttenlocher, Jon Kleinberg, and Xiangyang Lan. 2006. "Group Formation in Large Social Networks: Membership, Growth and Evolution." in *Proc. 12th ACM SIGKDD Int'l Conf. on Knowledge Discovery and Data Mining*.
- Backstrom, Lars and Jon Kleinberg. 2014. "Romantic Partnerships and the Dispersion of Social Ties: A Network Analysis of Relationship Status on Facebook." in *17th*

- ACM Conference on Computer Supported Cooperative Work.*
- Bakshy, Eytan, Jake M. Hofman, Winter A. Mason, and Duncan J. Watts. 2011. "Everyone's an Influencer: Quantifying Influence on Twitter." in *Proceedings of the Fourth ACM International Conference on Web Search and Data Mining.*
- Bakshy, Eytan, Itamar Rosenn, Cameron Marlow, and Lada Adamic. 2012. *The Role of Social Networks in Information Diffusion.* Retrieved (<http://arxiv.org/abs/1201.4145>).
- Bantum, Erin O'Carroll and Jason E. Owen. 2009. "Evaluating the Validity of Computerized Content Analysis Programs for Identification of Emotional Expression in Cancer Narratives." *Psychological Assessment* 21:79–88.
- Bar-Gill, Oren and Elizabeth Warren. 2008. "Making Credit Safer." *University of Pennsylvania Law Review* 157(1).
- Bertrand, Marianne and Sendhil Mullainathan. 2004. "Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination." *American Economic Review* 94(4):991–1013.
- Bhutta, Neil, Jacob Goldin, and Tatiana Homono. 2016. "Consumer Borrowing After Payday Loan Bans." *Journal of Law and Economics* forthcoming.
- Blei, David M., Andrew Y. Ng, and Michael I. Jordan. 2003. "Latent Dirichlet Allocation." *Journal of Machine Learning Research* 3:993–1022.
- Boivin, Diane B. et al. 1997. "Complex Interaction of the Sleep-Wake Cycle and Circadian Phase Modulates Mood in Healthy Subjects." *Archives of General Psychiatry* 54:143–52.
- Bolger, Niall, Angelina Davis, and Eshkol Rafaeli. 2003. "Diary Methods: Capturing Life as It Is Lived." *Annual Review of Psychology* 54:579–616.
- Bollen, Johan, Alberto Pepe, and Huina Mao. 2010. "Modeling Public Mood and Emotion: Twitter Sentiment and Socioeconomic Phenomena." in *Proceedings of the 19th International World Wide Web Conference.*
- Bond, Robert M. et al. 2012. "A 61-Million-Person Experiment in Social Influence and Political Mobilization." *Nature* 489(7415):295–98.
- Borgatti, Stephen P. and Daniel S. Halgin. 2011. "On Network Theory." *Organization Science.*
- Boutyline, Andrei and Robb Willer. 2011. *The Social Structure Of Political Echo Chambers: Ideology Leads To Asymmetries in Online Political Communication Networks.*
- boyd, danah and Kate Crawford. 2012. "Six Provocations for Big Data." *Information, Communication, & Society* 15(5):662–79.
- boyd, danah, Scott A. Golder, and Gilad Lotan. 2010. "Tweet, Tweet, Retweet: Conversational Aspects of Retweeting on Twitter." in *Proceedings of the Forty-Third Hawaii International Conference on System Sciences (HICSS-43).*
- Bradley, Margaret M. and Peter J. Lang. 1999. *Affective Norms for English Words (ANEW): Stimuli, Instruction Manual and Affective Ratings.* Gainesville, FL.
- Brashears, Matthew E. 2013. "Humans Use Compression Heuristics to Improve the Recall of Social Networks." *Nature Scientific Reports* 1513(3).
- Breiman, Leo. 2001. "Statistical Modeling: The Two Cultures." *Statistical Science* 16(3):199–231.

- Brewer, Marilynn B. and Michael D. Silver. 2000. "Group Distinctiveness, Social Identification, and Collective Mobilization." Pp. 153–71 in *Self-Identity and Social Movements*, edited by S. Stryker, T. J. Owens, and and Robert W. White. University of Minnesota Press.
- Burt, Ronald S. 1992. *Structural Holes: The Social Structure of Competition*. Harvard University Press.
- Burt, Ronald S. 1997. "A Note on Social Capital and Network Content." *Social Networks* 19:355–73.
- Butts, Carter T. 2009. "Revisiting the Foundations of Network Analysis." *Science* 325:414–16.
- Cassar, Alessandra, Luke Crowley, and Bruce Wydick. 2007. "The Effect of Social Capital on Group Loan Repayment: Evidence from Field Experiments." *The Economic Journal* 117:F85–106.
- Centola, Damon. 2010. "The Spread of Behavior in an Online Social Network Experiment." *Science* 329:1194–97.
- Centola, Damon. 2011. "An Experimental Study of Homophily in the Adoption of Health Behavior." *Science* 334(6060):1269–72.
- Centola, Damon and Michael Macy. 2007. "Complex Contagions and the Weakness of Long Ties." *American Journal of Sociology* 113(3):702–34.
- Cha, Meeyoung, Hamed Haddadi, Fabricio Benevenuto, and Krishna P. Gummadi. 2010. "Measuring User Influence in Twitter: The Million Follower Fallacy." in *International Conference on Weblogs and Social Media (ICWSM)*.
- Chao, Elaine L. and Kathleen P. Utgoff. 2006. *100 Years of U.S. Consumer Spending*.
- Chen, Kay-Yut, Scott A. Golder, Tad Hogg, and Cecilia Zenteno. 2008. "How Do People Respond to Reputation: Ostracize, Price Discriminate or Punish?" in *Second IEEE Workshop on Hot Topics in Web Systems*.
- Choi, Boi, Robert Kraut, and Mark Fichman. 2008. *Matching People and Groups: Recruitment and Selection in Online Games*.
- De Choudhury, Munmun, Winter A. Mason, Jake M. Hofman, and Duncan J. Watts. 2010. "Inferring Relevant Social Networks from Interpersonal Communication." *Proceedings of the 19th international conference on World wide web - WWW '10* 301.
- Clark, Lee Anna, David Watson, and Jay Leeka. 1989. "Diurnal Variation in the Positive Affects." *Motivation and Emotion* 13(3):205–34.
- Compton, Ryan, David Jurgens, David Allen, Delia Mocanu, and Alessandro Vespignani. 2013. *Social Networks by Minimizing Total Variation*.
- Conover, M. D. et al. 2011. "Political Polarization on Twitter." in *International Conference on Weblogs and Social Media (ICWSM)*.
- Contractor, Noshir. 2013. "Some Assembly Required: Leveraging Web Science to Understand and Enable Team Assembly." *Philosophical Transactions of the Royal Society A* 371(1987).
- Currier, Erin et al. 2015. *The Precarious State of Family Balance Sheets Project Team*.
- Daan, Serge, Domien G. M. Beersma, and Alexander A. Borbely. 1984. "Timing of Human Sleep: Recovery Process Gated by a Circadian Pacemaker." *American*

- journal of physiology. Regulatory, integrative and comparative physiology.* 15:R161--R183.
- Daft, Richard L. and Robert H. Lengel. 1986. "Organizational Information Requirements, Media Richness and Structural Design." *Management Science* 32(5):554–71.
- danah boyd and Nicole Ellison. 2007. "Social Network Sites: Definition, History, and Scholarship." *Journal of Computer-Mediated Communication* 13(1):n.p.
- Das, Sauvik and Adam Kramer. 2013. "Self-Censorship on Facebook." in *International Conference on Weblogs and Social Media (ICWSM)2*.
- Dean, Jeffrey and Sanjay Ghemawat. 2004. "MapReduce: Simplified Data Processing on Large Clusters." in *OSDI'04: Sixth Symposium on Operating System Design and Implementation*. San Francisco, CA.
- Derman, Emanuel. 2013. "The Young Person's Guide to Pricing and Hedging." 1–84.
- Digrazia, Joseph, Karissa Mckelvey, Johan Bollen, and Fabio Rojas. 2013. *More Tweets, More Votes: Social Media as a Quantitative Indicator of Political Behavior*.
- DiMaggio, Paul, Eszter Hargittai, W. Russell Neuman, and John P. Robinson. 2001. "Social Implications of the Internet." *Annual Review of Sociology* 27:307–36.
- DiMaggio, Paul and Hugh Louch. 1998. "Socially Embedded Consumer Transactions: For What Kinds of Purchases Do People Most Often Use Networks?" *American Sociological Review* 63(5):619–37.
- Dodds, Peter Sheridan and Christopher M. Danforth. 2010. "Measuring the Happiness of Large-Scale Written Expression: Songs, Blogs, and Presidents." *Journal of Happiness Studies* 11:441–56.
- Dodds, Peter Sheridan, Roby Muhamad, and Duncan J. Watts. 2003. "An Experimental Study of Search in Global Social Networks." *Science* 301:827–29.
- Doleac, Jennifer L. and Luke C. D. Stein. 2013. "The Visible Hand: Race and Online Market Outcomes." *Economic Journal* 123(572):469–92.
- Duncan, Otis Dudley. 1966. "Path Analysis: Sociological Examples." *American Journal of Sociology* 72(1):1–16.
- Eagle, Nathan, Michael W. Macy, and Rob Claxton. 2010. "Network Diversity and Economic Development." *Science* 328:1029–31.
- Edelman, Benjamin and Michael Luca. 2014. "Digital Discrimination: The Case of Airbnb.com." *Harvard Business School* 21.
- Edin, Kathryn and Laura Lein. 1997a. *Making Ends Meet: How Single Mothers Survive Welfare and Low-Wage Work*. New York: Russell Sage Foundation.
- Edin, Kathryn and Laura Lein. 1997b. "Work, Welfare and Single Mothers' Economic Survival Strategies." *American Sociological Review* 62(2):253–66.
- Ehrenreich, Barbara. 2001. *Nickel and Dimed: On (Not) Getting By in America*. New York: Henry Holt and Company.
- Emerson, Richard M. 1972. "Exchange Theory, Part {I} {I}." Pp. 58–87 in *Sociological Theories in Progress, Vol. 2*, edited by J. Berger, M. Zelditch, and B. Anderson. Houghton Mifflin.
- Entwisle, Barbara, Katherine Faust, Ronald R. Rindfuss, and Toshiko Kaneda. 2007. "Networks and Contexts: Variation in the Structure of Social Ties." *American*

- Journal of Sociology* 112(5):1495–1533.
- Erickson, Tom. 1999. "Persistent Conversation: An Introduction." *Journal of Computer-Mediated Communication* 4(4).
- Feliciano, Cynthia, Belinda Robnett, and Golnax Komaie. 2009. "Gendered Racial Exclusion Among White Internet Daters." *Social Science Research* 38:39–54.
- Fischer, Claude S. 2009. "The 2004 GSS Finding of Shrunken Social Networks: An Artifact?" *American Sociological Review* 74(4):657–69.
- Flynn, Francis J., Ray E. Reagans, and Lucia Guillory. 2010. "Do You Two Know Each Other? Transitivity, Homophily and the Need for (Network) Closure." *Journal of Personality and Social Psychology* 99(5):855–69.
- Forsythe, William C., Edward J. Rykiel Jr., Randal S. Stahl, Hsin-i Wu, and Robert M. Schoolfield. 1995. "A Model Comparison for Daylength as a Function of Latitude and Day of Year." *Ecological Modelling* 80:87–95.
- Fourcade, Marion and Kieran Healy. 2013. "Classification Situations: Life-Chances in the Neoliberal Era." *Accounting, Organizations and Society* 38(8):559–72.
- Freeman, Linton C. 1992. "Filling in the Blanks: A Theory of Cognitive Categories and the Structure of Social Affiliation." *Social Psychology Quarterly* 55(2):118–27.
- Freund, Yoav and Robert E. Schapire. 1997. "A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting." *Journal of Computer and System Sciences* 55(1):119–39.
- Friedman, Eric and Paul Resnick. 2001. "The Social Cost of Cheap Pseudonyms." *Journal of Economics and Management Strategy* 10(2):173–99.
- Furnham, Adrian and R. Rajamanickam. 1992. "The Protestant Work Ethic and Just World Beliefs in Great Britain and India." *International Journal of Psychology* 27(January):401–16. Retrieved (<http://www.tandfonline.com/doi/abs/10.1080/00207599208246905>).
- Gayo-Avello, Daniel. 2012. "No, You Cannot Predict Elections with Twitter." *IEEE Internet Computing* 16(6):91–94.
- Geertz, Clifford. 1962. "The Rotating Credit Association: A 'Middle Rung' in Development." *Economic Development and Cultural Change* 10(3):241–63.
- Gilbert, Eric and Karrie Karahalios. 2009. "Predicting Tie Strength With Social Media." in *Proceedings of the ACM Conference on Human Computer Interaction (CHI)*.
- Gladwell, Malcolm. 2000. *The Tipping Point: How Little Things Can Make a Big Difference*. Little, Brown and Company.
- Glaser, Barney G. and Anselm L. Strauss. 1967. *The Discovery of Grounded Theory: Strategies for Qualitative Research*. Chicago: Aldine Publishing Company.
- Goffman, Erving. 1959. *The Presentation of Self in Everyday Life*. Anchor.
- Golder, Scott A. and Michael W. Macy. 2011. "Diurnal and Seasonal Mood Vary with Work, Sleep and Daylength Across Diverse Cultures." *Science* 333:1878–81.
- Golder, Scott A., Dennis Wilkinson, and Bernardo A. Huberman. 2007. "Rhythms of Social Interaction: Messaging in a Massive Online Network." in *Communities and Technologies 2007*, edited by C. Steinfield, B. T. Pentland, M. Ackerman, and N. Contractor. Springer.

- Golder, Scott A. and Sarita Yardi. 2010. "Structural Predictors of Tie Formation in Twitter: Transitivity and Mutuality." in *Proceedings of the Second IEEE International Conference on Social Computing*. Minneapolis, MN.
- González-Bailón, Sandra, Javier Borge-Holthoefer, Alejandro Rivero, and Yamir Moreno. 2011. "The Dynamics of Protest Recruitment through an Online Network." *Scientific Reports* 1:1–7.
- Graeber, David. 2011. *Debt: The First 5,000 Years*. Brooklyn, New York: Melville House Publishers.
- Granovetter, Mark. 1973. "The Strength of Weak Ties." *American Journal of Sociology* 78:1360–80.
- Grinter, Rebecca E. and Leysia Palen. 2002. "Instant Messaging in Teen Life." *Proceedings of the 2002 ACM Conference on Computer-Supported Cooperative Work*.
- Guseva, Alya. 2008. *Into the Red: The Birth of the Credit Card Market in Post-Communist Russia*. Stanford University Press.
- Guseva, Alya and Akos Rona-Tas. 2001. "Uncertainty, Risk, and Trust: Russian and American Credit Card Markets Compared." *American Sociological Review* 66(5).
- Hampton, Keith and Barry Wellman. 2003. "Neighboring in Netville: How the Internet Supports Community and Social Capital in a Wired Suburb." *City & Community* 2(4):277–311.
- Hargittai, Eszter. 2010. "Digital Na(t)ives? Variation in Internet Skills and Uses among Members of the Net Generation." *Sociological Inquiry* 80(1):92–113.
- Harrington, Brooke. 2008. *Pop Finance*. Princeton, NJ: Princeton University Press.
- Harris, K. M. et al. 2009. "The National Longitudinal Study of Adolescent Health: Research Design."
- Hasler, Brant P., Matthias R. Mehl, Richard R. Bootzin, and Simine Vazire. 2008. "Preliminary Evidence of Diurnal Rhythms in Everyday Behaviors Associated with Positive Affect." *Journal of Research in Personality* 42:1537–46.
- Hastie, Trevor, Robert Tibshirani, and Jerome Friedman. 2009. *The Elements of Statistical Learning: Data Mining, Inference and Prediction*. 2nd ed. New York: Springer.
- Hechter, Michael. 1988. *Principles of Group Solidarity*. University of California Press.
- Henrich, Joseph, Steven J. Heine, and Ara Norenzayan. 2010. "The Weirdest People in the World?" *Behavioral and Brain Sciences* 33:61–83.
- Herring, Susan C. 1999. "Interactional Coherence in CMC." *Journal of Computer-Mediated Communication* 4(4).
- Hof, Robert. 2006. "Prosper: The eBay of Loans?" *BusinessWeek*, February.
- Hollan, Jim and Scott Stornetta. 1992. "Beyond Being There." *Proceedings of the SIGCHI conference on Human factors in computing systems - CHI '92* 119–25. Retrieved (<http://portal.acm.org/citation.cfm?doid=142750.142769>).
- Holley, Peter. 2016. "Republican Lawmaker Wants to Ban Welfare Recipients from Buying Steak and Lobster." *Washington Post* 1. Retrieved (<https://www.washingtonpost.com/news/wonk/wp/2016/02/23/republican-lawmaker-wants-to-ban-welfare-recipients-from-buying-steak-and-lobster/>).

- Holley, Peter and Elahe Izadi. 2015. "Kansas Bans Welfare Recipients from Seeing Movies, Going Swimming on Government's Dime." *Washington Post* 5–8. Retrieved (<https://www.washingtonpost.com/blogs/govbeat/wp/2015/04/06/kansas-wants-to-ban-welfare-recipients-from-seeing-movies-going-swimming-on-governments-dime/>).
- Homans, George C. 1958. "Social Behavior as Exchange." *American Journal of Sociology* 63(6):597–606.
- Homans, George C. 1961. *Social Behavior: Its Elementary Forms*. New York: Harcourt Brace Jovanovich.
- Honeycutt, Courtenay and Susan C. Herring. 2009. "Beyond Microblogging: Conversation and Collaboration via Twitter." in *Proceedings of the Forty-Second Hawaii International Conference on System Sciences (HICSS-42)*.
- Horrigan, John. 2009. *Home Broadband Adoption 2009*.
- Huberman, Bernardo A. 2012. "Big Data Deserve a Bigger Audience." 482(16 February 2012):308.
- Huberman, Bernardo A., Christoph H. Lock, and Ayse Onculer. 2004. "Status As a Valued Resource." *Social Psychology Quarterly* 67(1):103–14.
- Imbens, Guido W. and Joshua D. Angrist. 1994. "Identification and Estimation of Local Average Treatment Effects." *Econometrica* 62(2):467–75.
- Jernigan, Carter and Behram F. T. Mistree. 2009. "Gaydar: Facebook Friendships Expose Sexual Orientation." *First Monday* 14(10).
- Kadet, Anne. 2007. "The Banker Next Door." *SmartMoney*.
- Katz, Elihu and Paul Lazarsfeld. 1955. *Personal Influence*. New York: Free Press.
- Kirschbaum, C. and D. Hellhammer. 1989. "Salivary Cortisol in Psychobiological Research: An Overview." *Neuropsychobiology* 22:150–69.
- Kollock, Peter. 1999. "The Production of Trust in Online Markets." in *Advances in Group Processes*, vol. 16, edited by E. J. Lawler, M. Macy, S. Thye, and H. A. Walker. Greenwich, CT: JAI Press.
- Kossinets, Gueorgi and Duncan J. Watts. 2006. "Empirical Analysis of an Evolving Social Network." *Science* 311(88):88–90.
- Kramer, Adam D. I. 2010. "An Unobtrusive Behavioral Model Of 'gross National Happiness.'" in *Proceedings of the 28th international conference on Human factors in computing systems*.
- Kraut, Robert and Sara Kiesler. 2003. "The Social Impact of Internet Use." *Psychological Science Agenda* (Summer):8–10.
- Krebs, Valdis. 2008. "A Network of Books About Recent US Politics Sold by the Online Bookseller Amazon.com." Retrieved (<http://www.orgnet.com/2008>).
- Kricheli-katz, Tamar and Tali Regev. 2016. "How Many Cents on the Dollar? Women and Men in Product Markets." *Science Advances* 2(19 February).
- Kriplean, Travis, Ivan Beschastnikh, David McDonald, and Scott A. Golder. 2007. "Community, Consensus, Coercion, Control: CS*W or How Policy Mediates Mass Participation." in *ACM Group 2007*. Sanibel Island, FL.
- Kriplean, Travis, Ivan Beschastnikh, and David W. McDonald. 2008. "Articulations of WikiWork: Uncovering Valued Work in Wikipedia through Barnstars." in

- Proceedings of the ACM Conference on Computer-Supported Cooperative Work*. San Diego, CA.
- Krueger, Joachim. 2001. "Null Hypothesis Significance Testing: On the Survival of a Flawed Method." *American Psychologist* 56(1):16–26. Retrieved (<http://doi.apa.org/getdoi.cfm?doi=10.1037/0003-066X.56.1.16>).
- Kuhn, Thomas. 1962. *The Structure of Scientific Revolutions*. 3rd ed. University of Chicago Press.
- Kumar, Sanjeev. 2007. "Bank of One: Empirical Analysis of Peer-to-Peer Financial Marketplaces." in *Americas Conference on Information Systems*.
- Kwak, Haewoon, Changhyun Lee, Hosung Park, and Sue Moon. 2010. "What Is Twitter, a Social Network or a News Media?" Pp. 591–600 in *Proceedings of the 19th International World Wide Web Conference (WWW2010)*. ACM.
- Lam, R. W. and R. D. Levitan. 2000. "Pathophysiology of Seasonal Affective Disorder: A Review." *Journal of Psychiatry & Neuroscience* 25(5):469–80.
- Lazer, David et al. 2009. "Computational Social Science." *Science* 323:721–23.
- van der Leij, Marco and Sanjeev Goyal. 2011. "Strong Ties in a Small World." *Review of Network Economics* 10(2).
- Leskovec, Jure and Eric Horvitz. 2008. "Planetary-Scale Views on a Large Instant-Messaging Network." Pp. 915–924 in *Proceedings of the 17th International World Wide Web Conference*. ACM.
- Leskovec, Jure, Daniel Huttenlocher, and Jon Kleinberg. 2010. "Signed Networks in Social Media." in *CHI 2010*.
- Lewis, Kevin. 2015. "Three Fallacies of Digital Footprints." *Big Data & Society* 2(2):1–4. Retrieved August 12, 2016 (<http://bds.sagepub.com/lookup/doi/10.1177/2053951715602496>).
- Lewis, Kevin, Marco Gonzalez, and Jason Kaufman. 2011. "Social Selection and Peer Influence in an Online Social Network." *Proceedings of the National Academy of Sciences of the United States of America* 109(1):68–72. Retrieved March 2, 2013 ([http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3252911&tool=pmc entrez&rendertype=abstract](http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3252911&tool=pmc.entrez&rendertype=abstract)).
- Lewis, Kevin, Jason Kaufman, Marco Gonzalez, Andreas Wimmer, and Nicholas Christakis. 2008. "Tastes, Ties, and Time: A New Social Network Dataset Using Facebook.com." *Social Networks* 30:330–42.
- Lieber, Ron. 2011. "The Gamble of Lending Peer to Peer." *The New York Times*.
- Lyman, Peter and Nina Wakeford. 1999. "Going into the (Virtual) Field." *American Behavioral Scientist* 43(3):359–76.
- Macy, Michael W. and Robb Willer. 2002. "From Factors to Actors: Computational Sociology and Agent-Based Modeling." *Annual Review of Sociology* 28(1):143–66.
- Manski, Charles F. 1993. "Identification of Endogenous Social Effects: The Reflection Problem." *The Review of Economic Studies* 60(3):531–42.
- Marsden, Peter V. 1990. "Network Data and Measurement." *Annual Review of Sociology* 16:435–63.
- Mason, Winter and Siddharth Suri. 2011. "Conducting Behavioral Research on Amazon's Mechanical Turk." *Behavior research methods* 1–23.

- Mason, Winter and Duncan J. Watts. 2009. "Financial Incentives and the Performance of Crowds." in *Proceedings of the ACM SIGKDD Workshop on Human Computation*.
- Mayer, Adalbert and Steven L. Puller. 2008. "The Old Boy (and Girl) Network: Social Network Formation on University Campuses." *Journal of Public Economics* 92(June):329–47.
- McFarland, Daniel, Kevin Lewis, and Amir Goldberg. 2016. "Sociology in the Era of Big Data: The Ascent of Forensic Social Science." *The American Sociologist* 47(1):12–35. Retrieved August 12, 2016 (<http://link.springer.com/10.1007/s12108-015-9291-8>).
- McPherson, Miller. 2004. "A Blau Space Primer: Prolegomenon to an Ecology of Affiliation." *Industrial and Corporate Change* 13(1):263–80.
- McPherson, Miller, Lynn Smith-Lovin, and James M. Cook. 2001. "Birds of a Feather: Homophily in Social Networks." *Annual Review of Sociology* 27:415–44.
- Menchik, Daniel A. and Xiaoli Tian. 2008. "Putting Social Context into Text: The Semiotics of E-Mail Interaction." *American Journal of Sociology* 114(2):332–70.
- Mikolov, Tomas, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. "Efficient Estimation of Word Representations in Vector Space." Retrieved (<http://arxiv.org/abs/1301.3781>).
- Milgram, Stanley. 1967. "The Small-World Problem." *Psychology Today* 1(1):61–67.
- Mislove, Alan, Sune Lehmann, Yong-Yeol Ahn, Jukka-Pekka Onnela, and J.Niels Rosenquist. n.d. "Pulse of the Nation: U.S. Mood Throughout the Day Inferred from Twitter."
- Mohr, John W. and Petko Bogdanov. 2013. "Introduction—Topic Models: What They Are and Why They Matter." *Poetics* 41(6):545–69.
- de Montjoye, Yves-Alexandre, César Hidalgo, Michel Verleysen, and Vincent D. Blondel. 2013. "Unique in the Crowd: The Privacy Bounds of Human Mobility." *Scientific reports* 3:1376.
- Murray, Greg, Nicholas B. Allen, and John Trinder. 2001. "A Longitudinal Investigation of Seasonal Variation in Mood." *Chronobiology International* 18(5):875–91.
- Nie, Norman H. and D.Sunshine Hillygus. 2002. "The Impact of Internet Use on Sociability: Time-Diary Findings." *IT & Society* 1(1):1–20.
- Norvig, Peter. 2011. "On Chomsky and the Two Cultures of Statistical Learning." Retrieved (<http://norvig.com/chomsky.html>).
- O'Connor, Brendan, Ramnath Balasubramanyan, Bryan R. Routledge, and Noah A. Smith. 2010. "From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series." in *Proceedings of the International AAAI Conference on Weblogs and Social Media*. Washington, DC.
- Onnela, Jukka-Pekka et al. 2007. "Structure and Tie Strengths in Mobile Communication Networks." *Proceedings of the National Academy of Sciences of the United States of America* 104(18):7332–36.
- Paccagnella, Luciano. 1997. "Getting the Seats of Your Pants Dirty: Strategies for Ethnographic Research on Virtual Communities." *Journal of Computer-Mediated*

- Communication* 3(1).
- Pang, Bo and Lillian Lee. 2008. "Opinion Mining and Sentiment Analysis." *Foundations and Trends in Information Retrieval* 2(1-2):1-135.
- Peifer, Jared L. 2011. "Morality in the Financial Market? A Look at Religiously Affiliated Mutual Funds in the USA." *Socio-Economic Review* 9(2):235-59. Retrieved August 12, 2016 (<http://ser.oxfordjournals.org/cgi/doi/10.1093/ser/mwq024>).
- Pennebaker, J. W., M. E. Francis, and R. J. Booth. 2001. *Linguistic Inquiry and Word Count (LIWC): LIWC2001*. Mahwah: Lawrence Erlbaum Associates.
- Pinch, Trevor J. and Wiebe E. Bijker. 1984. "The Social Construction of Facts and Artefacts: Or How the Sociology of Science and the Sociology of Technology Might Benefit Each Other." *Social Studies of Science* 14(3):399-441.
- Podolny, Joel M. 2001. "Networks as Pipes and Prisms of the Market." *American Journal of Sociology* 107(1):33-60.
- Poon, Martha. 2009. "From New Deal Institutions to Capital Markets: Commercial Consumer Risk Scores and the Making of Subprime Mortgage Finance." *Accounting, Organizations and Society* 34(5):654-74.
- Pope, Devin G. and Justin R. Sydnor. 2011. "What's in a Picture? Evidence of Discrimination from Prosper.com." *Journal of Human Resources* 46(1).
- Portal, Abu Dhabi Government. 2010. "Working Hours Policy."
- Della Posta, Daniel, Yongren Shi, and Michael W. Macy. 2013. *Why Do Liberals Drink Lattes?*
- Postmes, Tom and Russell Spears. 2002. "Behavior Online: Does Anonymous Computer Communication Reduce Gender Inequality?" *Personality and Social Psychology Bulletin* 28(8).
- Preece, Jennifer and Ben Shneiderman. 2009. "The Reader-to-Leader Framework: Motivating Technology-Mediated Social Participation." *AIS Transactions on Human-Computer Interaction* 1(1):13-32.
- Pustejovsky, James E. and James P. Spillane. 2009. "Question-Order Effects in Social Network Name Generators." *Social Networks* 31(4):221-29.
- Rainie, Lee and Barry Wellman. 2012. *Networked: The New Social Operating System*. Cambridge, MA: MIT Press.
- Rand, David G. 2012. "The Promise of Mechanical Turk: How Online Labor Markets Can Help Theorists Run Behavioral Experiments." *Journal of theoretical biology* 1-8.
- Renton, Peter. 2016. "Prosper Lays Off 28% of Its Workforce and Closes Salt Lake City Office." *Lendacademy.com (blog)* 26-29. Retrieved (<http://www.lendacademy.com/prosper-lays-off-28-workforce-closes-salt-lake-city-office/>).
- Robinson, John P. 2011. "IT Use and Leisure Time Displacement." *Information, Communication and Society* 14(4):495-509.
- Robinson, Laura. 2011. "Information Channel Preferences and Information Opportunity Structures." *Information, Communication and Society* 14(4):472-94.
- Robnett, Belinda and Cynthia Feliciano. 2011. "Patterns of Racial-Ethnic Exclusion by Internet Daters." *Social Forces* 89(3):807-28.

- Romero, Daniel M., Brendan Meeder, and Jon Kleinberg. 2011. "Differences in the Mechanics of Information Diffusion across Topics: Idioms, Political Hashtags, and Complex Contagion on Twitter." in *Proceedings of the 20th International World Wide Web Conference (WWW2011)*.
- Rosenthal, Norman E. et al. 1984. "Seasonal Affective Disorder: A Description of the Syndrome and Preliminary Findings With Light Therapy." *Archives of General Psychiatry* 41(1):72–80.
- Rosenthal, Norman E. 2006. *Winter Blues*. The Guilford Press.
- Salganik, Matthew J., Peter Sheridan Dodds, and Duncan J. Watts. 2006. "Experimental Study of Inequality and Unpredictability in an Artificial Cultural Market." *Science* 311:854–56.
- Salganik, Matthew J. and Duncan J. Watts. 2009. "Web-Based Experiments for the Study of Collective Social Dynamics in Cultural Markets." *Topics in Cognitive Science* 1:439–68.
- Schor, Juliet B. 1999. *The Overspent American: Why We Want What We Don't Need*. Harper Perennial.
- Sears, David O. 1986. "College Sophomores in the Laboratory: Influences of a Narrow Data Base on Social Psychology's View of Human Nature." *Journal of Personality and Social Psychology* 51(3):515–30.
- Seegerstrom, S. C. and S. E. Sephton. 2010. "Optimistic Expectancies and Cell-Mediated Immunity: The Role of Positive Affect." *Psychological Science* 21(3):448–55.
- Servon, Lisa. 2017. *The Unbanking of America: How the New Middle Class Survives*. Houghton Mifflin Harcourt.
- Shalizi, Cosma Rohilla and Andrew C. Thomas. 2011. "Homophily and Contagion Are Generically Confounded in Observational Social Network Studies." *Sociological Methods and Research* 40(2):211–39.
- Shannon, Claude. 1956. "The Bandwagon." *IRE Transactions on Information Theory* 2(1).
- Shaw, Ryan. 2015. "Big Data and Reality." *Big Data & Society* 2(2):1–4. Retrieved August 12, 2016 (<http://bds.sagepub.com/lookup/doi/10.1177/2053951715608877>).
- Simpson, Brent and Tucker McGrimmon. 2008. "Trust and Embedded Markets: A Multi-Method Investigation of Consumer Transactions." *Social Networks* 30(1):1–15. Retrieved August 18, 2016 (<http://linkinghub.elsevier.com/retrieve/pii/S0378873307000366>).
- Smith, Aaron. 2011. *13% of Online Adults Use Twitter*. Retrieved (<http://pewinternet.org/Reports/2011/Twitter-Update-2011.aspx>).
- Smith, Aaron. 2012. *The Best (and Worst) of Mobile Connectivity*.
- State, Bogdan, Bruno Abrahao, and Karen Cook. 2012. "From Power to Status in Large Scale Online Exchanges." in *Proc. 4th ACM Conference on Web Science (WebSci)*.
- Stearns, David L. 2011. *Electronic Value Exchange: Origins of the Visa Electronic Payment System*. London: Springer.
- Steelman, Aaron. 2006. "Bypassing Banks." *Econ Focus*.

- Stone, Arthur A. et al. 2006. "A Population Approach to the Study of Emotion: Diurnal Rhythms of a Working Day Examined With the Day Reconstruction Method." *Emotion* 6(1):139–49.
- Sunstein, Cass R. 2001. *Republic.com*. Princeton University Press.
- Tajfel, Henri and John C. Turner. 1986. "The Social Identity Theory of Intergroup Behavior." Pp. 7–24 in *Psychology of Intergroup Relations*, edited by S. Worchel and L. W. Austin. Nelson-Hall.
- Taylor, Lindsay Shaw, G. A. Mendelsohn, Andrew T. Fiore, and Coye Cheshire. 2011. "Out of My League: A Real-World Test of the Matching Hypothesis." *Personality and Social Psychology Bulletin* 37:942–54.
- Terman, Michael and Jiuang Su Terman. 2005. "Light Therapy." in *Principles and Practice of Sleep medicine*, edited by M. H. Kryger, T. Roth, and W. C. Dement. Elsevier.
- Traud, Amanda L., Eric D. Kelsic, Peter J. Mucha, and Mason A. Porter. 2010. *Comparing Community Structure to Characteristics in Online Collegiate Social Networks*.
- Travers, Jeffrey and Stanley Milgram. 1969. "An Experimental Study of the Small World Problem." *Sociometry* 32(4):425–43.
- Tyler, Tom. 2003. "Why Do People Rely on Others? Social Identity and the Social Aspects of Trust." in *Trust in Society, Russell Sage Foundation Series on Trust*, edited by K. S. Cook. Russell Sage Foundation.
- Ugander, Johan, Lars Backstrom, Cameron Marlow, and Jon Kleinberg. 2012. "Structural Diversity in Social Contagion." *Proceedings of the National Academy of Sciences of the United States of America* 109(16):5962–66.
- Ugander, Johan, Brian Karrer, Lars Backstrom, and Cameron Marlow. 2011. *The Anatomy of the Facebook Social Graph*.
- Vittengl, Jeffrey R. and Craig S. Holt. 1998. "A Time-Series Diary Study of Mood and Social Interaction." *Motivation and Emotion* 22(3):255–75.
- Wacquant, Loïc. 2002. "Scrutinizing the Street: Poverty, Morality, and the Pitfalls of Urban Ethnography." *American Journal of Sociology* 107(6):1468–1532.
- Walther, Joseph B. 2007. "Selective Self-Presentation in Computer-Mediated Communication: Hyperpersonal Dimensions of Technology, Language, and Cognition." *Computers in Human Behavior* 23:2538–57.
- Wang, Jing et al. 2011. "Focused on the Prize: Characteristics of Experts in Massive Multiplayer Online Games." *First Monday* 16(8).
- Warren, Elizabeth and Amelia Warren Tyagi. 2003. *The Two-Income Trap: Why Middle-Class Mothers and Fathers Are Going Broke*. New York: Basic Books.
- Watts, Duncan J. 2004. "The 'New' Science of Networks." *Annual Review of Sociology* 30:243–70.
- Watts, Duncan J. 2012. *Everything Is Obvious: How Common Sense Fails Us*. Crown Business.
- Weber, Ingmar, Venkata R. Kiran Garimella, and Alaa Batayneh. 2013. "Secular vs . Islamist Polarization in Egypt on Twitter." in *IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*.
- Weber, Max. 1904. *The Protestant Ethic and the Spirit of Capitalism*. London:

- Routledge.
- Weber, Max. 1922. *Economy and Society*. edited by G. Roth and C. Wittich. University of California Press.
- Webster, Tom. 2010. *Twitter Usage In America: 2010: The Edison Research/Arbitron Internet and Multimedia Study*.
- Wellman, Barry and Keith Hampton. 1999. "Living Networked On and Offline." *Contemporary Sociology* 28(6):648–54.
- Welser, Howard T. et al. 2011. "Finding Social Roles in Wikipedia." *Proceedings of the 2011 iConference*.
- Weng, Lilian, Filippo Menczer, and Yong-Yeol Ahn. 2013. "Virality Prediction and Community Structure in Social Networks." *Scientific reports* 3:2522. Retrieved November 11, 2013 (<http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3755286&tool=pmc-entrez&rendertype=abstract>).
- Willer, R., F. J. Flynn, and S. Zak. 2012. "Structure, Identity, and Solidarity: A Comparative Field Study of Generalized and Direct Exchange." *Administrative Science Quarterly* 57(1):119–55.
- Wimmer, Andreas and Kevin Lewis. 2010. "Beyond and Below Racial Homophily: ERG Models of a Friendship Network Documented on Facebook." *American Journal of Sociology* 116(2):583–642.
- Wright, Sewall. 1934. "The Method of Path Coefficients." *The Annals of Mathematical Statistics* 5(3):161–215.
- Xie, Wei, Cheng Li, Feida Zhu, Ee-Peng Lim, and Xueqing Gong. 2012. "When a Friend in Twitter Is a Friend in Life." *Proceedings of the 3rd Annual ACM Web Science Conference on - WebSci '12* 344–47. Retrieved (<http://dl.acm.org/citation.cfm?doid=2380718.2380763>).
- Yardi, Sarita, Daniel M. Romero, Grant Schoenebeck, and Danah Boyd. 2010. "Detecting Spam in a Twitter Network." *First Monday* 15(1).
- Zachary, Wayne W. 1977. "An Information Flow Model for Conflict and Fission in Small Groups." *Journal of Anthropological Research* 33:452–73.
- Zeckhauser, Richard. 2006. "Investing in the Unknown and Unknowable." *Capitalism and Society* 1(2).
- Zizzo, Daniel John. 2010. "Experimenter Demand Effects in Economic Experiments." *Experimental Economics* 13(1):75–98.