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Variations on a Theme of Within-Person Variation

By

Arman Daniel Catterson

A dissertation submitted in partial satisfaction of the
requirements for the degree of
Doctor of Philosophy
in
Psychology
in the
Graduate Division
of the
University of California, Berkeley

Committee in charge:

Professor Oliver P. John, Chair
Professor Serena Chen
Professor Dana R. Carney

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Abstract

Variations on a Theme of Within-Person Variation

by

Arman Daniel Catterson

Doctor of Philosophy in Psychology

University of California, Berkeley

Professor Oliver P. John, Chair

Variation characterizes much of everyday life. People's thoughts, feelings, and behaviors are not static, but change depending on who they are, where they are, and with whom they are. For personality psychologists interested in describing this variation, new and low-cost methods of assessment can describe how people differ from each other on average, as well as how people differ from their own average across multiple real-life situations and social interactions. Researchers use such *within-person* methods to develop sophisticated models of personality, emotion, and self-esteem that aim to represent real-life variance in experience.

In this dissertation, I extend this within-person approach to the study of emotion regulation and social hierarchy. Researchers consider emotion regulation and social hierarchy to be domains of psychological life that serve important social functions. Yet few studies have examined these domains in real-life social interactions, and no research has examined how these domains change across a person's everyday life.

In Chapter 1, I introduce the topic of within-person variation more formally with a review of key concepts and differences from other approaches to psychology. Specifically, I argue that a within-person approach is fundamental for researchers to understand psychological processes. I then summarize the methods of assessment and analysis that I will use in this dissertation, and develop three broad research questions about within-person processes that guide my empirical research.

In Chapter 2, I present research on within-person variation in expressive

suppression - a strategy that people use to regulate their emotions by hiding expressions in the face and body. In contrast to past research that emphasizes the negative consequences of *stable* suppression use, I find evidence that suppression use can serve adaptive functions when used in specific situations.

In Chapter 3, I focus my within-person approach on the study of social hierarchy. Although past theory differentiates social power (a person's ability to exert influence or control in a situation) from social status (a person's respect or reputation) and from social class (a person's rank in society), these three related dimensions of social hierarchy are not well-differentiated at the empirical level. In this chapter, I demonstrate ways in which accounting for within-person variation supports existing theory and offer new insights that differentiate these related hierarchical dimensions.

Together, the findings reported in these two chapters demonstrate the prevalence and potential of within-person variation in psychological research. In Chapter 4, I summarize the major findings in the two empirical chapters, discuss the broader implications and limitations of this research and within-person methods of assessment more broadly, and conclude with suggested ideas for future research.

Dedicated to my family.

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INTRODUCTION

Bus rides in the Bay Area present many opportunities to observe the variety of daily life. The Alameda County #12 bus, for example, winds its way from downtown Oakland up through the gentrified hills of Lower Piedmont and Upper Rockridge before turning onto an impoverished stretch of Martin Luther King Blvd that ends in the heart of downtown Berkeley. In the span of fifty minutes, one harried passenger late for work may think of herself as the least privileged, least conscientious, and most neurotic rider at one stop, and may suddenly see herself as someone on the other ends of the distribution when some less fortunate passenger appears on the bus at the next stop.

Within-person variation describes the person's changing psychological experience. Such variation characterizes much of everyday life, from the situations and relationships that people find themselves in, to the thoughts, feelings and behaviors in those situations. The degree to which a person experiences within-person variation depends on where they are, who they are, and who they are with.

Yet as variation dominates our daily life, the statistical average dominates the daily life of psychological researchers. Social psychologists measure the talkativeness of participants who have been manipulated to hold power, and compare that average rating to the average talkativeness of participants who have been manipulated to lack power (Galinsky, Gruenfeld, & Magee, 2003). Similarly, personality psychologists report correlational relationships to show people who are more extraverted than the average person also tend to experience a greater subjective sense of power than the average person (Anderson & Berdhal, 2002).

These hypothetical patterns of effects are illustrated in the top half of Figure 1. The left-hand graph (Figure 1A) represents mean-level differences in talkativeness (y-axis) for one person who was experimentally manipulated to be high in power (dark gray) and another person who was experimentally manipulated to be low in social power (light gray). This graph describes that one person who was manipulated to be high in power was rated as more talkative than one person who was manipulated to be low in power. (If this graph was based on a *sample* of people where were manipulated to be high or low in power, it could also resemble the graph in Figure 1B, and should include error bars that describe an

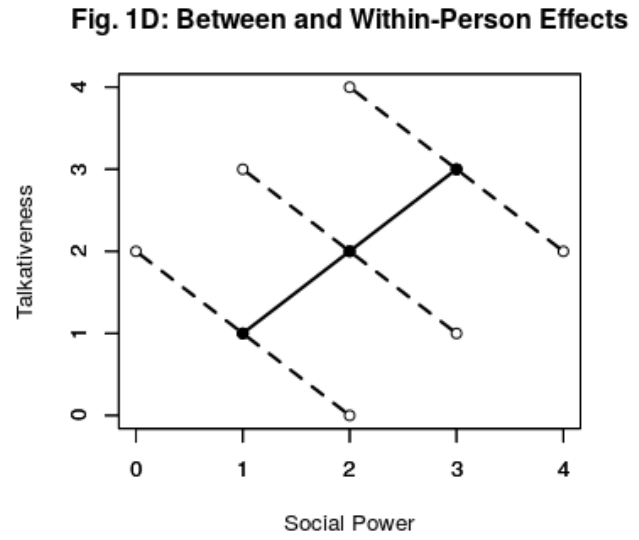
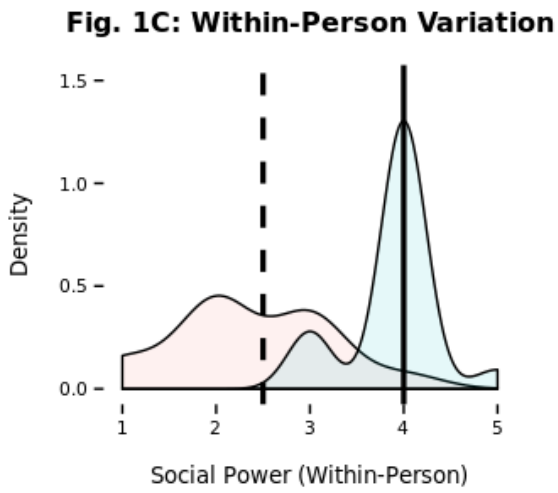
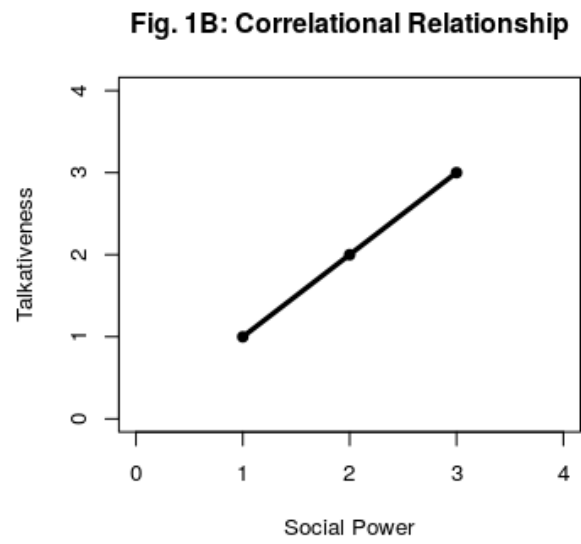
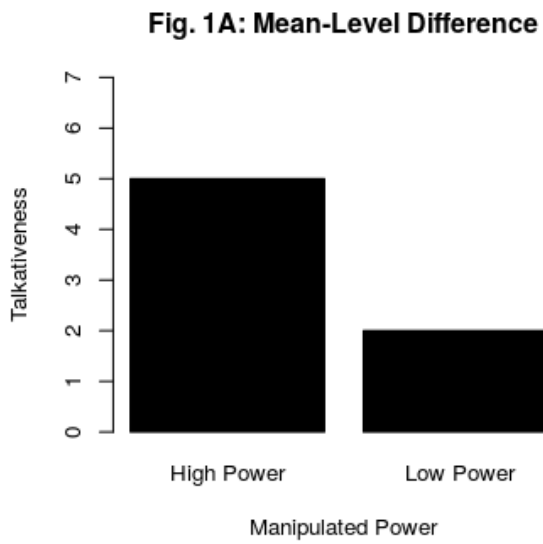


Figure 1. Four approaches to psychological variation in social power.

estimate of the amount that the average other person would vary from the estimated level of talkativeness.)

The right hand graph (Figure 1B) represents the mean-level correlational relationship between three people who, on average, are low or high in social power (x-axis) and three people who on average are low or high in talkativeness (y-axis). This graph describes that someone who sees her or himself as higher in power than average is likely to be more

talkative than average.

Though based on hypothetical data, these graphs are no doubt familiar to readers of this dissertation. Researchers across different disciplines emphasize mean-level differences or mean-level correlational relationships in many psychological constructs. The mean is a good statistic to use when researchers are interested in understanding patterns in *general* tendencies in how people are measured to behave, or *general* responses to a specific (and manipulable) feature of the situation. However, for researchers who seek to explain how people think, feel, and act across a variety of situations, the mean is not sufficient because it is static: it cannot capture how people change.

This emphasis on averages is not limited to traditional methods and research in psychology. The much-ballyhooed predictive success attributed to baseball analytics depends on mean performance metrics (c.f., Lewis, 2004), whereas modern "big data" analytic approaches (e.g., Kosinski, Stillwell, & Graepel, 2013) distill large, multi-dimensional matrices of complex combinations of online human behavior into a single line estimate analogous to the mean of a sample. When variance is reported in academic journals, it is often referred to as "error" and commonly reported in parentheses alongside the mean as an implicit reminder of its second-class statistical status.

Historically, there have been few methods of assessment and analysis that allowed researchers to focus on variance. In 1955, Gordon Allport wrote, "Precisely here we find the reason why so many psychologists fail to take an interest in the existential richness of human life. Methods, they say, are lacking" (p. 11).

In this dissertation, I seek to utilize modern methods to focus on *within-person variance*: defined as a person's variation in a specific construct across multiple time points and social contexts. Such methods are not new, and have been used by researchers over the past few decades to study cognitive processes like flow, self-evaluations, emotions and affective states, and personality (e.g., Csikszentmihalyi & Hunter, 2003; Fleeson, 2001; Nezlek, 2005; Zelinsky & Larsen, 2010). My dissertation research applies this method in two novel domains of psychological research - social hierarchy and emotion regulation.

In Chapter 1, I explain within-person variation in more detail by describing ways that it characterizes psychological life, ways that

psychologists can now easily assess and analyze this variance, and articulate three research questions that can be applied to psychological theory and research that more accurately capture that "existential richness of human life." For example, Figure 1B graphs the same two participants that were graphed in Figure 1A, but maintains the natural within-person variation, whereas Figure 1D graphs the same correlational relationship displayed in Figure 1C at the level of the individual (solid line) and situation (dashed line). I explain these graphs in more detail in Chapter 1; for now it should be apparent that each of the two bottom graphs in Figure 1 contain more information than the graphs on top, and also expresses relationships at different levels of analysis.

In Chapter 2, I focus on social hierarchy, and test whether social power, status, and class - three hierarchical constructs characterized by considerable overlap in the existing empirical literature - might be better distinguished by features at the within-person level rather than at the between-person level. Does the relationship between power and class change across situations? Are there situations in which a person might be high in power but low in class?

In Chapter 3, I apply this within-person framework to test novel predictions about how people will use emotion regulation strategies in everyday life. How much do people vary in their use of different emotion regulation strategies? What individual difference and situational features explain these differences? Might an emotion regulation strategy previously considered "bad" actually be "good" when used in certain situations?

In Chapter 4, I summarize how the findings reported in this dissertation inform psychological research more generally, and outline several ideas for future research on within-person variance. Given the momentum in the field, more powerful and detailed methods of assessment will soon become available to researchers seeking to understand how people vary in real life. I therefore conclude with a brief discussion about what consequences these advances might hold, and possible inherent limitations to intensive, repeated-measurement designs.

In the Appendix, I provide detailed documentation about the measures used and methods employed in distribution and data cleaning, as well as R code for all analyses and figures. These materials are intended for future journal editors and readers interested in learning more about the specifics of the methods and analyses employed for each study.

CHAPTER 1: VARIANCE IN PSYCHOLOGICAL RESEARCH

That the anxiety we feel over, say, a looming dissertation milestone is at all similar to the anxiety felt on a first date or to the anxiety of driving on a highway for the first time or the anxiety that our evolutionary ancestors might have felt searching for water or shelter demonstrates an incredible quality of human life. Despite no upgrades to our basic anatomical and physiological hardware, our software - that broad network of psychological constructs that drive human affect, cognition, and behavior - is able to handle a radically different environment than the one in which it originally evolved to handle. Evolutionary approaches to psychology assert that constructs such as extraversion, emotion, and hierarchy were passed down the evolutionary tree because they served as flexible tools that helped our ancestors adapt to ever-changing environments (Buss, 1991; Keltner & Haidt, 1999; Henrich & Gil-White, 2001). Indeed, genetic variation itself is considered by many to be one of the fundamental mechanisms that drives life (Darwin, 1859; see also: Dawkins, 1976; Buss, 1999).

Variation also drives the psychological researcher's life. A world with no variation would be one in which the psychologist's career might resemble that of a computer scientist who first learns the codified rules of human behavior (i.e., the programming language) and then works to manipulate the code to achieve her or his goal. Instead, psychologists are faced with the challenging task of observing a startling variety in human thoughts, feelings, and behaviors, and sorting through or synthesizing this noise to develop organized psychological principles.

The Problem of Variation

In order to study variation in a given psychological dimension, psychologists employ methods that systematically *remove* variance in what they believe to be dimensions that are unrelated to the phenomenon of interest. The way that psychologists approach studying variance in one dimension by minimizing it in other dimensions depends on her or his research tradition. For example, personality psychologists (whose interests lie in understanding the broad individual differences between people that influence behavior) remove extraneous variation by (1) averaging multiple items to create a composite personality score (i.e., removing variance across measures of a construct) and (2) instructing participants to rate what they are like "*in general*" (i.e., removing variance due to features of the situation). Social psychologists, in contrast, want to understand the ways that specific situations influence

human behavior and thus utilize methods that artificially create variance in one specific feature of a situation (via experimental manipulation), while ideally holding all other individual difference and situational variables constant (i.e., removing variance across persons).

Both research traditions advance the science of psychology by understanding between-person differences. However, the attempt to study variance in one dimension (i.e., individual differences) by eliminating or ignoring variance in other dimensions (i.e., situations, relationships) often leaves both personality and social psychology disconnected from the real-life behaviors and psychological processes that they seek to explain. Many common psychological methods are therefore not able to *jointly* measure the manifestation of internal traits as expressed across multiple situations (Buss, 1987; Fleeson & Gallagher, 2009; Funder, 2009). Traditional methods may allow personality and social psychology researchers to study individual differences and situational influences on behavior, respectively, but do not allow researchers to examine how individual differences are manifest across different situations.

This limitation was inherent to the person-situation debate, a decades-long argument between psychologists over whether global measures of personality were relevant predictors of a person's behavior, or whether behavior was determined mostly by features of the situation (e.g., Mischel, 1968; Kenrick & Funder, 1988). As acknowledged by most psychologists today (and as would likely seem common-sense to any non-psychologist), *both* individual differences and situational forces matter in determining human behavior (for a system of how these features interact, see Buss, 1986). By averaging over variance caused by situations, personality psychologists were not able to account for the influence of situations on behavior, and by controlling for individual differences, social psychologists were not able to account for the influence of individual differences on behavior.

That psychologists spent considerable energy engaged in a debate about the importance of differences between people and situations reflects a problem in depending on methods of study that isolate variance in one factor at the exclusion of others. However methodological advances now allow researchers to better represent real-life. For example, Fleeson (2001) demonstrated that there are substantial and reliable differences *between* people (in support of the personality approach to psychology) and substantial and reliable differences *within* how the person responds across different situations (in support of the social approach to psychology).

His integration of personality and social psychological research traditions via experience sampling not only provided empirical evidence to help settle the person-situation debate (Roberts & Pomerantz, 2004; Mischel, 2004; Fleeson, 2004), but has also since served as an analytic model that researchers use to describe variability in other constructs (e.g., Oishi, Diener, Napa Scollon, & Biswas-Diener, 2004; Kashdan & Rottenberg, 2010; Gruber, Kogan, Quoidbach, and Mauss, 2013).

Within-Person Variation

Definition and Use in Psychology

Within-person variation is defined as the way a person's thoughts, feelings, or behaviors can change in response to different situational or relationship contexts. Whereas *between-person* variation describes the differences in how people think, feel, or behave *on average*, within-person variation describes how a person varies from her or his own average. Someone with large within-person variation in a given psychological dimension would change a lot in that variable as she or he goes from one situation to another, whereas someone with little within-person variation would change less across different situations.

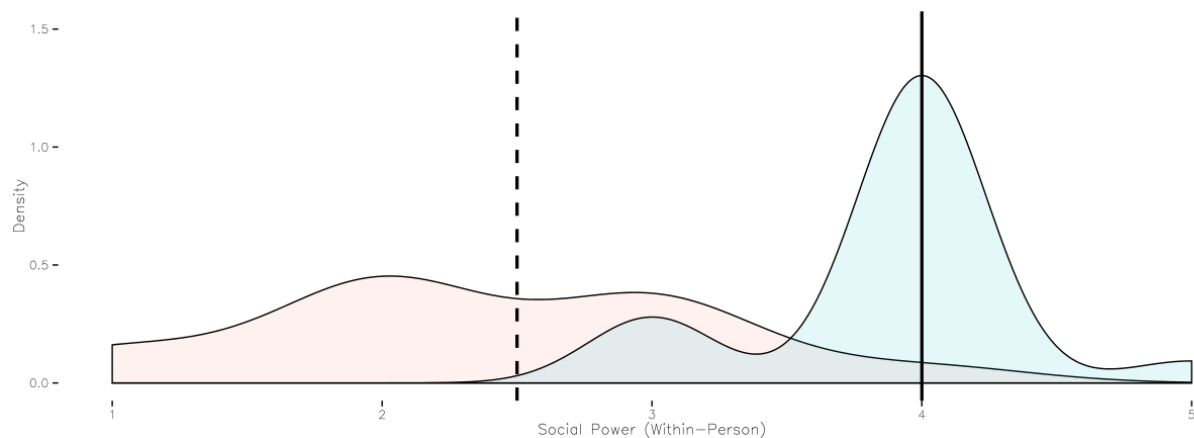


Figure 2. Example of within- and between-person variation in social power.

Figure 2 illustrates both within- and between-person variation in social power as density distributions for two people across multiple situations. Each distribution describes how one person rated her or his own social power across different situations. The vertical line that bisects each distribution illustrates the mean of that distribution (i.e., the person's average score). In this illustration, one person has greater average power than another person, which would describe a between-person difference.

In contrast, within-person variation is illustrated in the amount of spread between around each person's own average rating of power. Though the dark-gray person appears to hold more power on average than the light-gray participant, she or he also experiences greater variability in power, and even appears to hold less power at times than the dark-gray participant. Additional analyses and graphs might help researchers further explain when and why this variance occurs. Yet even this simple graph can illustrate the greater complexity that within-person approaches hold, and the way in which focusing on between-person, mean-level differences alone can mask important psychological differences.

Advances in Assessment: Capturing Within-Person Variability

Researchers use within-person methods to assess variation in a wide array of psychological constructs, such as positive or negative moods (Perunovic, Heller, & Rafaeli, 2007; Gruber, Kogan, Quoidbach, and Mauss, 2013), specific positive and negative emotional states such as happiness and well-being (Emmons, 1986; Csikszentmihalyi & Hunter, 2003; Killingsworth & Gilbert, 2010) and the Big Five personality dimensions (e.g., Fleeson, 2001/2007; Fleeson & Gallagher, 2009; Judge, Simon, Hurst, & Kelley, 2014). However studies that use within-person methods are less common than other methods, and for good reason: data on how multiple people respond and behave across multiple situations have been and continue to be difficult to collect.

Pioneers of the within-person approach tried a variety of methods (for a review, see Wilhelm, Perrez, & Pawlik, 2012). For example, in the 18th and 19th centuries there was a trend among scholars (notably, Darwin, in his 1877 "Biological Sketch of an Infant") to take daily notes about their children's physical, sensory, and emotional development. More recently, Barker and Wright (1951) recruited a group of observers to monitor a day in the life of the 7-year-old boy known as Raymond. Craik (2000) extended this method in his "lived-day approach" by recruiting research assistants to video tape participants as they navigated their daily responsibilities. These approaches suffered from a variety of methodological limitations; Craik (2000) himself wryly notes, "Obviously, following a person around with a video recorder all day has its inherent constraints as a field study method, particularly with regard to its reactivity" (p. 238). Nonetheless, these approaches represent early and earnest efforts to capture people's real-life psychological experiences.

More recent technological advances have reduced the barriers for researchers to attain intensive yet unobtrusive assessments in real-life.

One method, known as *experience sampling*, involves surveying participants' thoughts, feelings, and behaviors across multiple real-life situations (for reviews, see: Christensen, Barrett, Bliss-Moreau, Lebo, Kaschub, 2003; Conner et al., 2007; Conner, Tennen, Fleeson & Barrett, 2009). The original experience sampling methods were relatively expensive, and required people to carry beepers, notebooks, and pencils, enter responses in notebooks that they carried, and then turn these notebooks in at the end of the assessment period for researchers to analyze (a burden for participant, researcher, and research assistant).

Today, however, experience sampling studies are easily deployed by taking advantage of the smartphone. This ubiquitous device of modern society not only allows people to access information almost any place at any time, but also enables researchers to access participants in almost any place at any time (Lipsman, Aquino, & Flosi, 2013).

As the barriers to real-life assessment rapidly evaporate in the bright light of modern technology, researchers have been quick to adopt experience sampling methods in their own research. Figure 3 illustrates this exponential trend in terms of the number of studies published in psychology journals that contain the phrase "experience sampling" (the y-axis) as a function of time (the x-axis).

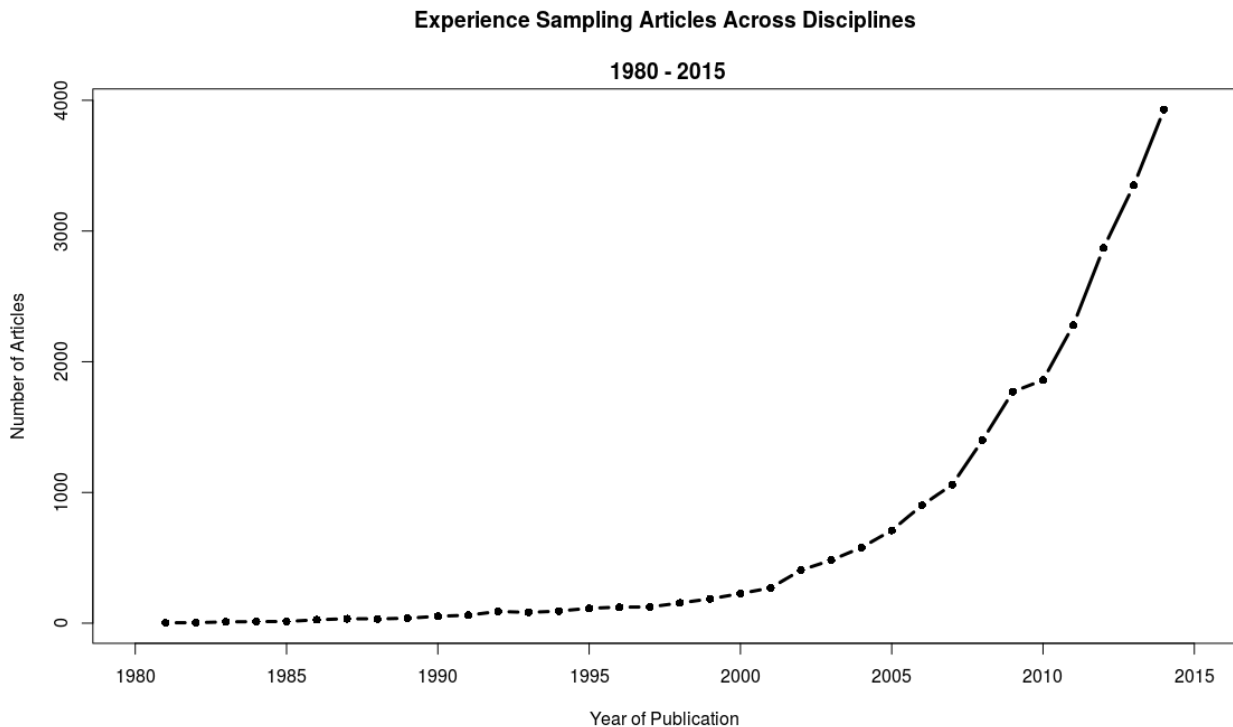


Figure 3. Trends in Experience Sampling Research.

Advances in Analysis: Modeling Within-Person Variability

Experience sampling methods not only allow researchers to understand psychological processes of interest at more detailed and ecologically valid level of analysis, but also to examine both *between-person effects* (i.e., variance explained by differences in what people are like in general) and *within-person effects* (i.e., variance explained by differences how the person responds across different times or situations) within the same study. These methods thus permit researchers to test novel hypotheses and address gaps in the literature caused by traditional reliance on individual difference or experimental methods.

Researchers interested in describing the *amount* of variability tend to aggregate experience sampling data by estimating the standard deviation of the participants' responses across multiple situations (e.g., Fleeson, 2001/2007; Gruber, Kogan, Quoidbach, and Mauss, 2013). On the one hand, this statistic allows researchers to describe the *amount* of within-person variation that people experience (i.e., the degree to which a person varies from his or her own average). On the other hand, estimating the standard deviation of a participant's score across situations reduces within-person variability into a between-person construct. By aggregating within-person variation (i.e., when a person is feeling extraverted in each situation) into a between-person effect (i.e., the extent to which a person is variable), researchers lose the ability to examine within-person processes - that very level of analysis at which life is lived and that researchers seek to understand via experience sampling methods.

To fully understand how people think, feel, and behave within situations, more advanced statistics are needed. Fortunately, around the same time that experience sampling methods were being developed by social scientists, statisticians began to develop new kinds of linear models that would help researchers unify between-person and within-person effects into one parsimonious statistical model of behavior.

In what he termed the "ecological fallacy," Robinson (1950) articulated a problem inherent to psychological research that uses between-person analyses to make inferences about within-person processes. For example, research that suggests people who tend to be high in power tend to be more talkative (a between-person effect) does not provide any information about whether people who are in situations where they are more powerful than they usually are are also more talkative than they usually are. Indeed, researchers might find that social power and talkativeness are negatively related at the within-person level, but positively related

at the between-person level: the two levels of analysis are conceptually and statistically orthogonal.

This concept is illustrated in Figure 4 by the contrast between the solid line, which describes a positive relationship between individual differences in power and talkativeness (a between-person effect), as well as a negative relationship between situations where people report having power and being talkative (a within-person effect). People who on average are high in social power are, on average, high in talkativeness. However, in situations where people feel more power than they do on average, people are less talkative than they are on average

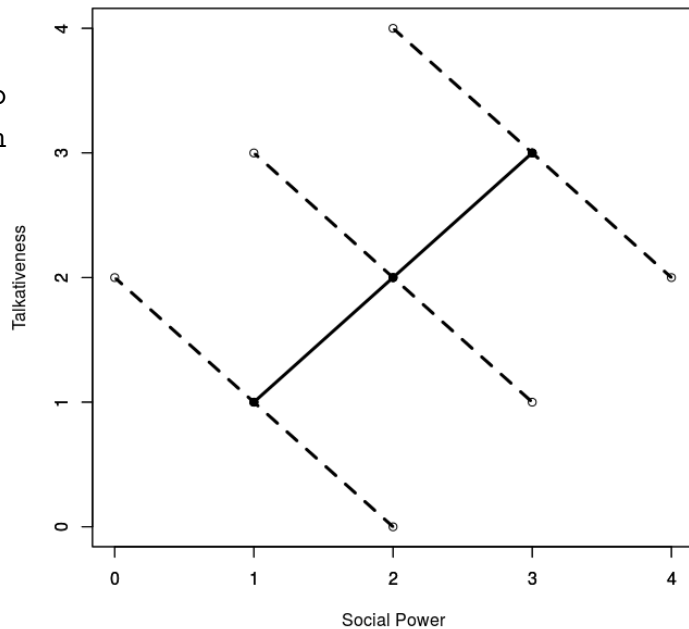


Figure 4. The ecological fallacy (Robinson, 1950)

Various methods were developed in an attempt to address the ecological fallacy (e.g., Davis, Spaeth, & Huson, 1961). However it wasn't until the 1980s that researchers had the statistical tools and computer processing power needed to simultaneously examine between- and within-person effects. These "multilevel" models (also called "random effects," "mixed effects," or "hierarchical" models) preserve both between- and within-person variability, and allow researchers to examine between- and within-person processes.

Three Research Questions that Capitalize on Within-Person Variation

Given these new technological and statistical methods, researchers are now able to more easily understand within-person processes. Below, I develop three research questions that multilevel models can address, and that will serve as a conceptual framework for my dissertation.

How much within-person variation is there? First, multilevel models are able to estimate the *amount* of within-person variation in a given construct. Unlike the "aggregate" approach, in which within-person variation is calculated as the standard deviation in a person's scores across the different assessments, multilevel models estimate unique

intercepts for each participant (i.e., a "random slope"), and describe the variance in these intercepts to estimate the between-person variance (Snijders, 2011). Within-person variance is described as the variance not explained by these between-person effects. Conceptually, this method is similar to the "aggregate" approach used by Fleeson (2001) and others, and should yield the same results. However, the multilevel approach is preferred from a statistical standpoint because it allows researchers to control for variables such as time that might violate important statistical assumptions (Scollon, Prieto, & Diener, 2009; Snijders, 2011).

Researchers can therefore use multilevel models to reliably estimate both between-person and within-person variance for psychological constructs. To provide a "benchmark" to help contextualize the amount of between- and within-person variance, I will compare estimated between- and within-person variances in related constructs, and will compare variances from this dissertation research to variances reported in past research.

What predicts within-person variation? Second, multilevel models preserve variability at the level of the situation (Scollon et al., 2009). This means researchers can measure other situational variables and use those variables to make predictions about when people vary at the situational level. For example, Killingsworth and Gilbert (2010) used experience sampling to measure variability in a person's level of happiness, amount of mind-wandering, and situational activity (i.e., what the person was doing), and found mind-wandering was related to decreased levels of happiness, even when accounting for what the person was doing.

In this dissertation, I used experience sampling methods to examine those features of persons, situations, and emotions that influence psychological constructs. Rather than take a kitchen sink approach, in which all potential predictors are thrown into a model to see which one best predicts the dependent variable of interest, I sought to test competing hypotheses based on past theory and research. Furthermore, in addition to examining the standardized relationships between constructs, I also report the percentage of within-person variance in a psychological dimension that is explained by the presence of other personality and situational factors.

What does within-person variation predict? Finally, researchers can also use multilevel models to answer questions about the consequences of within-person variability. Though experimentation is the preferred method of establishing causality, researchers can conduct time-lagged analyses to determine whether changes in one construct at one time point

predict changes in another construct at a future time point (Bolger & Laurenceau, 2013; Duckworth, Tsukayama, & May, 2010). For example, Killingsworth and Gilbert (2010) used time-lagged analyses to make the claim that mind-wandering causes decreases in happiness by demonstrating that mind-wandering predicted subsequent decreases in happiness, but levels of happiness did not predict subsequent changes in mind-wandering.

A final goal of this dissertation was to test whether variation at the within-person level holds different consequences for individuals than variation at the between-person level. Might existing psychological theory be succumbing to the ecological fallacy (Robinson, 1950), in which consequences at the between-person level may not necessarily hold at the level of the situation? Or do between-person approaches adequately account for the way in which a psychological dimension operates at the level of the situation?

The Present Research

Psychological Domains to Study at the Within-Person Level

In this dissertation, I utilized the assessment and analytic advantages of experience sampling methods and multilevel models in to extend these three questions about within-person variation and to further understand two psychological domains. The historical emphasis on mean-level differences is particularly problematic for psychological constructs that are defined by dynamic social and situational processes. Below, I summarize the two dynamic psychological constructs that served as the focus of this dissertation.

Chapter 2: Social Hierarchy. Hierarchical differences between social mammals have been a focus of a considerable amount of theory and research across research disciplines. Anthropological accounts of non-human primates describe interactions where one individual male in the group dominates others and enjoys increased reproductive success compared to lower-ranking males in the group (Altman et al., 1996; Cummings, 2005). Social theory describes a similar struggle between the people and institutions who control systems of production and the people who are controlled by those same systems (e.g., Marx, 1894; de Beauvoir, 1949; Bourdieu, 1996). Psychologists, in turn, examine the consequences of hierarchical differences on people's thoughts, feelings, and behaviors (e.g., Keltner, Anderson, & Gruenfeld, 2003; Piff et al., 2010; Adler, Epel, Castellazzo, & Ickovics, 2000; Kraus, Chen, & Keltner, 2011).

Typically ignored in this research, however, is an account of the dynamic nature of social hierarchy. One person's hierarchical standing is

not necessarily fixed, but is likely to change as a function of where they are, with whom they are, and how they feel. To better understand this natural variability in social hierarchy, I used experience sampling to describe within-person variation in social power, status, and class.

Chapter 3: Emotion Regulation. Emotion scholars have long recognized the importance of context to understanding emotional experiences, expressions, and social functions (Keltner & Haidt, 1999; Keltner & Kring, 1998; Frijda & Mesquita, 1994; Mauss, Levenson, McCarter, Wilhelm, & Gross, 2005). However, considerably less research has examined the way in which contextual features shape people's efforts to *regulate* these emotions. This dissertation will build on past theory and research on two emotion regulation strategies - suppression and reappraisal - to test whether the use and consequences of these strategies in real-life contexts might differ from the use of these strategies in experimental settings (e.g., Butler et al., 2003) or at the individual difference level (e.g., Gross & John, 2003).

Two Qualifications to the Current Research

Experience sampling methods have traditionally relied on self-report methods (Fleeson, 2001/2007; Nezlek & Kuppens, 2008; Killingsworth & Gilbert, 2010; Kuppens, Tuerlinckx, Russell, & Barrett, 2013), and my research in this dissertation is no different. Self-reports - flawed as they are - are meaningful, and represent one valid source of information about what people are like and how they will behave (Hogan, Hogan, & Roberts, 1996; Roberts, Kuncel, Shiner, Caspi, & Goldberg, 2009; Orth, Robins, & Roberts, 2008; Paulhus & Vazire, 2007). Though self-report methods have achieved a bad reputation in the field of psychology, they are more common in the field than many researchers recognize; self-reports are often used as the sole criterion by which to gauge the effects of an experimental manipulation or the validity of new "big data" methods and experimental designs (e.g., Kosinski, Stillwell, & Graepel, 2013). In the conclusion to this dissertation, I describe ways in which future experience sampling research might branch out to incorporate informant reports or behavioral measures (Vazire, 2006; 2010).

However, within-person analyses are inherently more complex than between-person analyses. In the interest of readability, I have elected to report summaries of statistical models in Chapters 2 and 3 that emphasize key findings from the results of more exploratory and comprehensive models. I have worked to ensure these results are both reliable (i.e., they generalize between samples) and valid (i.e., they reflect a priori

hypotheses). In addition, a complete account of the models tested for this dissertation, R code for all analyses, and links to download data are reported in the Appendices.

CHAPTER 2: A WITHIN-PERSON APPROACH TO SOCIAL HIERARCHY

Summary

Psychological theory suggests that social hierarchy is characterized by differences in social power, status, and class, yet few empirical articles account for how these related hierarchical states differ from each other. In this chapter, I study how social power, status, and class vary across a person's everyday life, and use this *within-person* approach to develop hypotheses about how these hierarchical dimensions differ from each other. In two experience sampling studies (total N = 106), I demonstrate that social power, status, and class exhibit considerable overlap at the stable individual difference level. However, these constructs differ in terms of their situational stability and antecedents. Specifically, I find evidence across both samples that these three dimensions of social hierarchy: (1) differ in their amount of within-person variation; (2) are less related at the level of the situation than at the level of the person; (3) each have unique patterns of effects across situations and social interactions; and (4) hold different associations with each other over time. Together, these studies provide empirical evidence that supports existing theory, and demonstrate how a within-person approach can help differentiate the effects of power, status, and class in ways that advance new ideas for future research on social hierarchy.

A Within-Person Approach to Social Hierarchy

A person's hierarchical standing in society is not fixed, but can change as a function of the person, situation, and time. A revolution replaces one monarch with another; a powerful banker (or academic) is rendered powerless when faced with his own child's temper tantrum; a chorus of clicks and shares makes a struggling band go "viral," the social dynamics of a group of students (or academics) shifts when the cool person leaves the room.

Such dynamic variation in people's subjective sense of social hierarchy is part of everyday life. However the majority of psychological research focuses on static hierarchical differences that characterize interactions between people or institutions. In this chapter, I take a first step to providing a situational account of how people vary in their subjective sense of hierarchy across real-life situations. Below, I outline a new conceptual approach that integrates existing theory and research on social hierarchy, and describe how this approach can advance hypotheses about how related hierarchical constructs such as power, status, and class differ from each other.

Power, Status, and Class: Three Dimensions of Hierarchy **Conceptual Clarity**

Psychological researchers typically focus their studies of social hierarchy on one of three related dimensions. One line of research extends from Fiske's (1993) article on social power, defined as a person's control over resources and ability to exert influence over others (Fiske, 1993; Fiske & Depret, 1996; Galinsky, Gruenfeld, & Magee., 2003; Keltner, Gruenfeld, & Anderson, 2003). Research from this tradition might examine how differential access to resources enable people with power to take greater risks, see the world optimistically, and express uninhibited behaviors that are more likely to represent their true selves (e.g., Anderson & Berdahl, 2002; Chen, Langner, & Mendoza-Denton, 2009; Chen, Lee-Chai, & Bargh, 2001; Kraus, Chen, & Keltner, 2011).

Other research focuses on the ways in which various perceptions can influence (and be influenced by) a person's social status, defined as respect and esteem in a social group (e.g., Anderson, John, Keltner, & Krings, 2001; Anderson & Kilduff, 2009; Berger, Cohen, & Zelditch, 1972). Research from this tradition might examine gender differences in the personality correlates of status attainment (Anderson, Srivastava, Beer, Spataro, & Chatman, 2006) or the ways in which people can achieve status

by adopting strategies that assert their dominance or prestige (Cheng, Tracy, Foulsham, Kingstone, & Henrich, 2013).

More recently, psychological researchers have turned their attention to the study of social class, defined as a person's objective or subjective rank in society (e.g., Adler et al., 1994; Kraus, Piff, Mendoza-Denton, Rheinschmidt, & Keltner, 2012). Research from this tradition might examine how differences in people's sense of their own social rank in society are associated with various cognitive, motivational, and behavioral tendencies, such as reduced feelings of dependence on others and greater tendency to behave in self-interested ways (e.g., Piff, Stancato, Côté, Mendoza-Denton, & Keltner, 2012).

Together, these research traditions on power, status, and class represent three broad dimensions of social hierarchy that are related, yet theoretically distinct in important ways (Blader & Chen, 2012/2014; Emerson, 1962; Ridgeway 2001). For example, Blader and Chen (2014) suggest that social power and status should be differentiated by their antecedents, behaviors, and consequences. Under their framework, one critical distinction between status and power lies in their antecedents, as status is considered to be based on others' judgments and evaluations (e.g., Anderson & Kilduff, 2009), whereas power is considered to be based on the person's own subjective or objective ability to exert influence and control in a situation (e.g., Anderson, John, & Keltner, 2012; Keltner, Gruenfeld, & Anderson, 2003; Magee & Galinsky, 2008). Less research has considered the differences between social class and either power or status, though Dubois, Rucker, and Galinsky (2015) recently point out that people from upper classes are more likely to have power via their increased wealth and more likely to have status via their increased rank than people from lower classes.

Muddled Methods

Despite such differentiation at the theoretical level, these hierarchical dimensions are not well-differentiated at the empirical level (Simon & Oakes, 2006). This lack of differentiation takes several different forms. Sometimes, researchers employ methods that are designed to measure or manipulate one hierarchical dimension that might also unintentionally measure or manipulate other hierarchical dimensions. For instance, Galinsky et al. (2008) primes participants with stereotypically high power words, such as "authority" and "boss" - words that could very well also prime status and class. Other common manipulations ask participants to write about a time when they felt high in power (e.g.,

Galinsky et al., 2003; 2008), yet it is likely that these recollections also involve a time when participants felt high in status or class.

Other times, researchers find evidence for similar patterns of effects that are labeled under different names. For example, researchers have found that increases in social power and social class are both associated with increases in testosterone (e.g., Sapolsky, 2004; Carney, Cuddy, & Yap, 2010) and a tendency to focus more on the self and less on others (e.g., Galinsky et al., 2006; Piff et al., 2012), that both social status and social power are associated with greater experience of positive emotion (e.g., Anderson & Berdahl, 2002; Steckler & Tracy, 2014), and that people tend to anchor their ratings of others' social power, status, and class to their own self-reports (Catterson, Carney, Chen, John, & Naumann, *under review*).

Some researchers are beginning to test hypotheses about the unique effects of specific hierarchical dimensions. For example, Fragale, Overbeck, and Neale (2011) differentiated participants' levels of power and status through an experimental manipulation, and found that people form less positive impressions of a high-power, low status target relative to other combinations. Dubois, Rucker, and Galinsky (2015) demonstrated that the apparent effects of social class on unethical behavior (Piff et al., 2012) were explained entirely by differences in social power.

Such research is beginning to develop a more nuanced understanding of social power, status, and class, and represents important progress in the science of social hierarchy. In contrast to past approaches that differentiate power, status, and class in terms of the unique antecedents, behaviors, and consequences associated with *stable* differences in each construct (Blader & Chen, 2014), I take an approach that examines *situational* differences - the extent to which power, status, and class change as a function of where the person is and who the person is with. Below, I describe how this approach might offer researchers a new explanation for how power, status, and class differ from each other across a wide variety of social contexts.

Situational Stability?

Theories of social hierarchical acknowledge that dimensions such as power, status, and class depend on a person's social context (e.g., Emerson, 1962; Galinsky, Gruenfeld, & Magee, 2003; Magee & Galinsky, 2008; Overbeck, 2010; Kraus, Chen, & Keltner, 2011). However, researchers still know very little about how these hierarchical dimensions change across people's everyday lives.

The few studies that examine change in social hierarchy tend to focus on the effects of longitudinal or manipulated change in hierarchy (e.g., Coie & Dodge, 1983; Cohn, 1978; Marr & Thau, 2014). This research thus does not offer an account of the everyday, moment to moment changes that characterize real-life. To date, no research has examined the extent to which and consequences of change in social hierarchy over time and place.

Instead, researchers are primarily interested in understanding stable differences in social hierarchy, and design studies that focus on comparisons between people who have been measured or manipulated to be high or low in a specific hierarchical dimension. Such methods are well-suited for researchers interested in examining the consequences associated with differences in hierarchy between people, but do not allow researchers to measure differences within-persons.

Questions and Predictions About Social Hierarchy Within-Persons

Are power, status, and class best characterized as stable individual differences? Will someone high in power in one situation be high in power across all situations? Or do these constructs vary and change depending on where the person is and who the person is with? To answer such questions, I focus on how hierarchical constructs such as power, status, and class vary across a person's everyday life. Whereas past approaches to social hierarchy generally emphasize the extent to which one person differs from another person on average (i.e., *between-person* differences), I examine the extent to which people differ from their own average across situations (i.e., *within-person* differences).

Within-person methods have helped researchers develop new theories and resolve long-standing debates (e.g., Denissen, Penke, Schmidt, & Van Aken, 2008; Fleeson, 2004; Micshel, 2004; Rottenberg & Gross, 2003). For example, researchers differentiate related affective states by the extent to which they change over time and place. Whereas an emotion is defined by fast affective reactions that serve as a response to specific features of a situation, a mood is defined by slow, long-lasting affective states that do not vary in response to situational features (Rottenberg & Gross, 2003).

However no research has used within-person methods to advance understanding of social hierarchy. Below, I outline three broad research questions generated by this within-person approach to social hierarchy that I test in the current research. In this chapter, I focus on social power, status, and class because they represent three dimensions of social

hierarchy that are the most common subjects of research (e.g., Magee & Galinsky, 2008; Blader & Chen, 2014).

Question 1: How Does Social Hierarchy Vary Within-Persons?

Past theory and research suggests that dimensions of social hierarchy may hold different patterns of within-person variation. For example, researchers typically describe social power to be a dimension of hierarchy that is rooted in a person's psychological construal of the situation (e.g., Anderson, John, & Keltner, 2012; Keltner, Gruenfeld, & Anderson, 2003; Galinsky et al., 2006). This suggests that people's perceptions of their own social power will change as the situation changes. In contrast, past theory on social class suggests that differences in who ranks high or low on the ladder are related to broad historical, cultural, and environmental forces (e.g., Marx, 1848; Wark, 2005; Weber, 1922/1978). This suggests that people's perceptions of their own social class will remain relatively stable as the situation changes.

It is less clear whether people will vary more or less in social status across different situations. On one hand, past theory and research on social status emphasizes that a person's reputation is based on evaluations made by other people (Anderson & Kilduff 2009; Blau, 1964). As people are often aware of others' evaluations of the self (Carlson, Vazire, & Furr, 2009), a person's subjective sense of social status should vary to the extent that those others' change. On the other hand, people are often seen consistently by others, particularly in terms of their status or reputation (e.g., Anderson & Shirako, 2008; Craik, 2009). If others' have consistent views about what a person's status is like, then self-perceptions of status may not change across situations even if a person is sensitive to others' evaluations.

Hypothesis 1: Dimensions of social hierarchy will differ in their amount of within-person variation. Based on this research, I expect that people will exhibit substantial within-person variation in social power. Compared to social power, I expect that people will exhibit significantly less within-person variation in social class. I do not hold specific predictions about the amount of within-person variation in social status relative to power or class.

Past research demonstrates that people differ in their average level of social power, status, and class (e.g., Anderson et al., 2001; Anderson, John, & Keltner, 2013; Kraus, Chen, & Keltner, 2011). Differences between-persons (i.e., how one person's average hierarchical standing differs from another person's average hierarchical standing) are conceptually and

statistically independent of within-person differences (i.e., how a person differs from his or her own average; Fleeson, 2001). Although I expect to find a certain amount of within-person variation in all three dimensions of social hierarchy, I also expect to find significant and stable individual differences in social power, status, and class.

Question 2: What Predicts Within-Person Variation in Social Hierarchy?

If there is substantial within-person variation in social hierarchy, then a next step is to try and explain this variance. Are these divergent patterns of within-person variation random noise, or are they explained by features of the situation in ways that are consistent with past research?

Hypothesis 2: Dimensions of social hierarchy will differ more in their correlational relationship at the within-person level than at the between-person level. If dimensions of social hierarchy hold unique patterns of variance across situations, then it is also likely that power, status, and class will differ from each other more at the within-person level than at the between-person level. That is, whereas someone who has high power on average should be likely to also have high status on average, it's likely that there are certain situations in which someone might have high power but not status.

Although past research has not tested this hypothesis, theoretical approaches to social hierarchy support this idea. Researchers often use highly contextualized and specific anecdotes to illustrate the ways in which constructs like status and power differ. For example, Keltner, Gruenfeld, and Anderson (2003) write that "it is possible to have power without status (e.g., the corrupt politician) and status without relative power (e.g., a readily identified religious leader in line at the Department of Motor Vehicles)", whereas Dubois, Stern, and Galinsky (2015) point to the Queen of England as someone who is high in class but has little power.

I expect to find more differentiation in dimensions of social hierarchy at the within-person level than at the between-person level. That is, the relationship between a person's average social power and the person's average social class should be stronger than the relationship between a person's social power in one situation and the person's social class in that same situation.

Hypothesis 3: Dimensions of social hierarchy will have different situational antecedents. Because power and status are considered to be based on specific situational or relationship contexts

(e.g., Keltner, Gruendfeld, & Anderson, 2003; Anderson, John, & Keltner, 2012; Overbeck & Park, 2010; Schmid Mast, 2010), a large percentage of variation in social power and status should be explained by variance in the situation. In contrast, because social class is considered to be based on broader social and environmental forces (e.g., Weber, 1978), I predict that variation in social class will not be explained by what the person was doing. Someone from a low class background is likely to feel low class across many situations.

Based on past theory and research that suggests social status is conferred to people by others (e.g., Weber, 1978; Simon & Oakes, 2006; Anderson & Kilduff 2009), I expect that differences in whether people are in social vs. non-social situations will explain more variance in social status than in either social power or social class. In contrast, less variance in social class and power should be explained by variation in the number of other people in the interaction.

Question 3: What Does Within-Person Variation in Social Hierarchy Predict?

If dimensions of social hierarchy are differentiated at the within-person level and hold different antecedents, then it is possible that they will also be associated with different outcomes. One unresolved question in research on social hierarchy is how dimensions such as social power, status, and class are related to each other over time. Do changes in social power lead people to experience greater status, or does status lead to power? Does power allow people to achieve higher rank and social class, or does class afford people greater power?

Hypothesis 4: Dimensions of social hierarchy will hold different consequences. If social class represents the broadest, most stable dimension of social hierarchy, then changes in social class should cause people to experience changes in social power and social status in future interactions. That is, someone who feels like they gained social class in one situation should be more likely to feel like they also gained social power in a future interaction than someone who feels like they lost social class.

In contrast, if social power and social status represent more variable dimensions of social hierarchy, then changes in these measures may not necessarily be related to changes in social class. Someone who feels like they have gained social power in one situation may or may not feel like they also gained social class in the next interaction.

Methods

To test these hypotheses, I examined people's subjective ratings of their social power, status, and class across real-life relationship contexts. I used an experience sampling paradigm to measure people's subjective ratings of different hierarchical dimensions in real-life situations in two independent samples. Experience sampling methods are common in research on within-person variation in personality and emotion, and allow researchers to examine psychological processes in real-life over time and across multiple situations (e.g., Fleeson, 2001; Nezlek & Kuppens, 2008).

Because participant population, assessment procedures, and measures of social hierarchy were identical across samples, I combined both samples into a single composite. Effects replicated across the two samples.

Participants

Participants were 106 (74% female) students at a large public university on the West Coast. On average, participants were 20.8 years old (SD = 2.2 years) and were of diverse ethnic backgrounds (42% Asian, 24% White, 11% Latino, 3% Black, 2% Middle Eastern, 6% Other, 12% did not report). Participants completed the study for partial course credit and personality feedback.

Procedures

Participants were sent text messages six times a day for six consecutive days on a fixed schedule at the hours of 10:00, 12:00, 14:00, 16:00, 18:00, and 20:00. Participant ratings were cleaned following guidelines and recommendations established in past experience sampling research (e.g., Christensen, Barrett, Bliss-Moreau, Lebo, & Kaschub, 2003). After cleaning procedures, 86% of ratings remained. An R script for all cleaning procedures is available in the Appendix.

Measures

At each time point, participants were asked a variety of questions about the objective features of the situation they were in and their subjective assessment of their personality, emotion, and social hierarchy in that situation. I report all available measures of social hierarchy administered during the study. A full list of other measures of personality and emotion that were administered in these samples is available in the Appendix.

Objective features of the situation. I first asked participants to describe the features of the situation that they were in when assessed.

Activity. I asked participants to rate what they were "doing in the

last 30 minutes (i.e., just before receiving this text)" from a list of possible options. This list was based common situations reported in development of the Day Reconstruction Method (Kahneman et al., 2004), has been used in past experience sampling research (Killingsworth & Gilbert, 2010), and includes a wide variety of situations such as "Housework", "Outdoors", "Hanging out with friends", and "Browsing the Internet."

Social interaction. I also asked participants to rate the number of other people they "were directly interacting with in this situation." Participants indicated whether they were alone (47% of completed responses), with one other person (19% of responses), with two other people (10% of responses), with three to four other people (11% of responses), with five to ten other people (6% of responses), with 11-20 other people (2% of responses), or in a group of more than 20 people (6% of responses).

Dimensions of social hierarchy. In each situation, I also asked participants to rate their self-perceptions of social hierarchy. All ratings were made on a scale from 1 (*Not at All*) to 5 (*Very Much*).

Social power. To assess social power ($M = 2.4$, $SD = 1.2$, $Range = 1 - 5$), I asked participants to rate the extent to which they "Had a great deal of power (e.g., could exert influence)."

Social status. To assess social status ($M = 2.4$, $SD = 1.2$, $Range = 1 - 5$), I asked participants to rate the extent to which they "Had a lot of social status (e.g., was respected by others)."

Social class. To assess social class ($M = 2.2$, $SD = 1.1$, $Range = 1 - 5$), I asked participants to rate the extent to which they "Were high in social class (e.g., had high rank in society)."

These ratings are graphed in Figure 5. The majority of students rated themselves as relatively low (i.e., below the midpoint of the scale) across all three measures of social hierarchy.

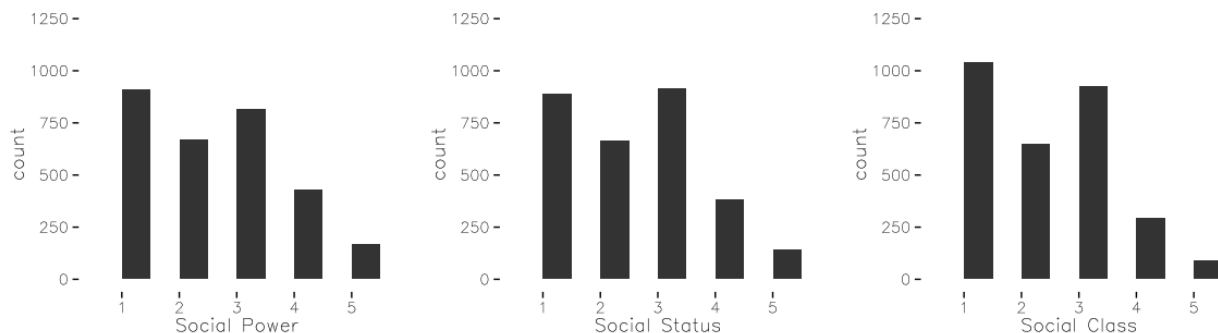


Figure 5. Histograms of dimensions of social hierarchy.

Results

Hypothesis 1: Dimensions of Social Hierarchy Differ in their Amount of Within-Person Variation

To test my first hypothesis, I used the lme4 package (Bates, Maechler, Bolker, & Walker, 2014) in R (version 3.1.2) to run a series of multilevel models that predict either social power, status, or class from a random intercept grouped by participant. This random intercept term describes the percentage of variance explained by *stable* individual differences in social hierarchy (i.e., between-person variance). The residual variance describes the extent to which dimensions of social hierarchy are *dynamic* (i.e., within-person variance).

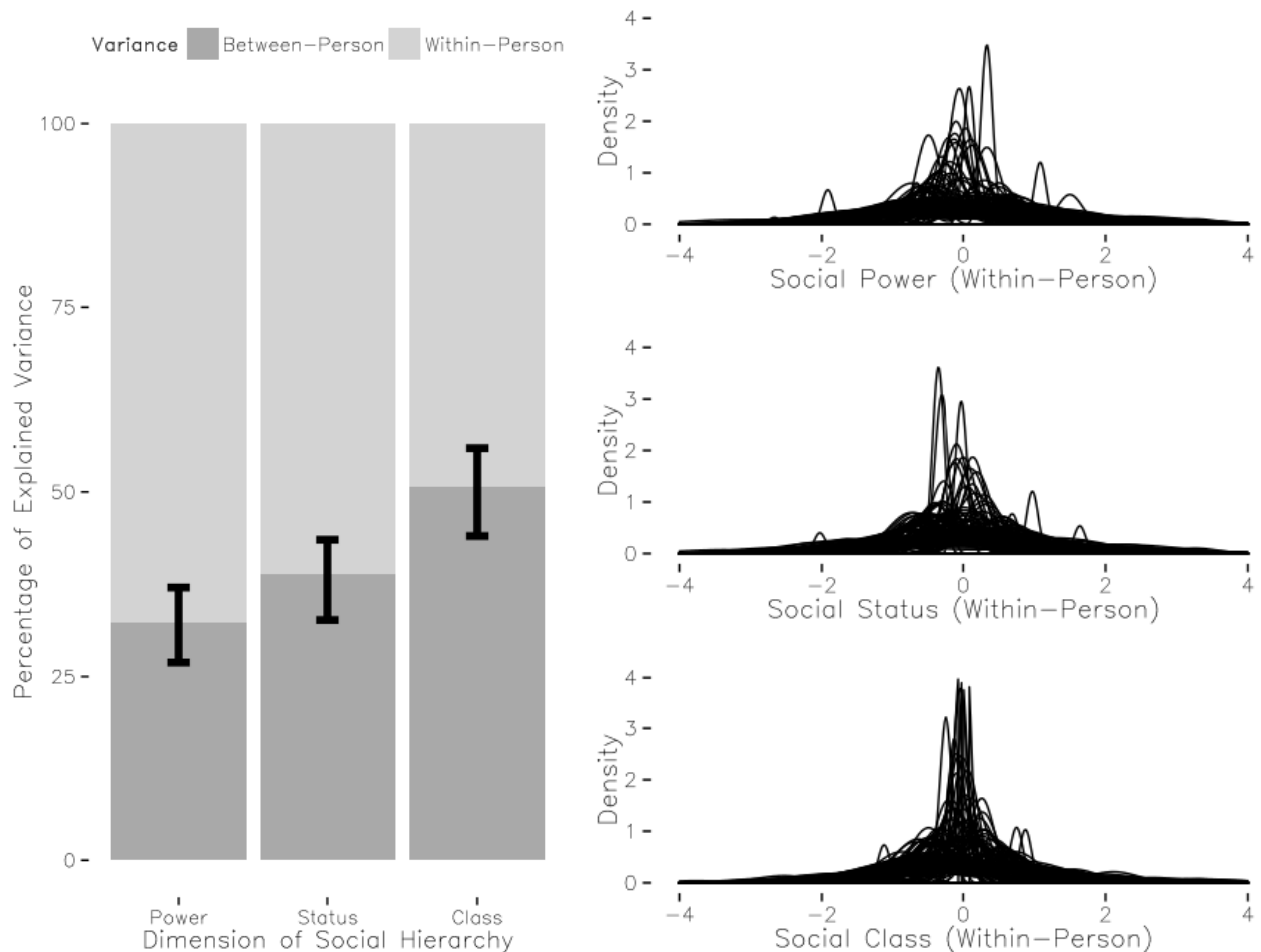


Figure 6. Between-person and within-person variance in dimensions of hierarchy. Note: error bars represent 95% Confidence Intervals estimated using bootstrapping (999 simulations; normal approximation).

As predicted, I found that dimension of social hierarchy differ in the extent to which they vary between- and within-persons. These effects are illustrated in the left-hand side of Figure 6, with the dark

gray bars representing the percentage of variance described by between-person effects, and the light gray bars representing the percentage of variance described by within-person effects. Social power exhibited the most within-person variance across situations ($\sigma^2 = 68\%$, 95% CI [64, 73]), followed by social status ($\sigma^2 = 61\%$, 95% CI [54, 68]), followed by social class, which exhibited the least within-person variance across situations ($\sigma^2 = 49\%$, 95% CI [44, 56]). Confidence intervals for these variance estimates were generated through bootstrapping (999 simulations; normal approximation), and suggest that the difference in between-person variance between social class and social power and status do not overlap, and thus are unlikely to be due to chance.

These findings suggest that all three dimensions of social hierarchy are characterized both by stable individual differences as well as substantial within-person variation. This within-person variance across situations is illustrated in the right-hand side of Figure 6, which depicts density distributions for social status, power, and class. Each line represents one participant's ratings of a specific hierarchical dimension across situations standardized by his or her own average. Although there is substantial variability in people's ratings of power, status, and class, the shape of these distributions illustrates that there is less overall variation in social class than either social power or status.

Hypothesis 2: Dimensions of Social Hierarchy Will Differ More in their Correlational Relationship at the Within-Person Level than the Between-Person Level

To test my second hypothesis, I calculated separate between-person and within-person effects for each construct. A between-person effect estimates a person's average rating across the experience sampling measures, and describes the extent to which a person is generally high or low in a given construct. A within-person effect describes the extent to which a person's specific situational rating of power, status, or class was above or below the person's own average rating of that same hierarchical dimension.

To determine whether social power, status, and class would differ more in their contextual relationship than their stable relationship, I tested a series of linear multilevel models that predicted variation in one from variation in between-person and within-person effects in another dimension. The results of these analyses are summarized in Figure 7, which illustrates the relationships among between-person differences in social

hierarchy (left panels) and the relationships among within-person differences in social hierarchy (right panels).

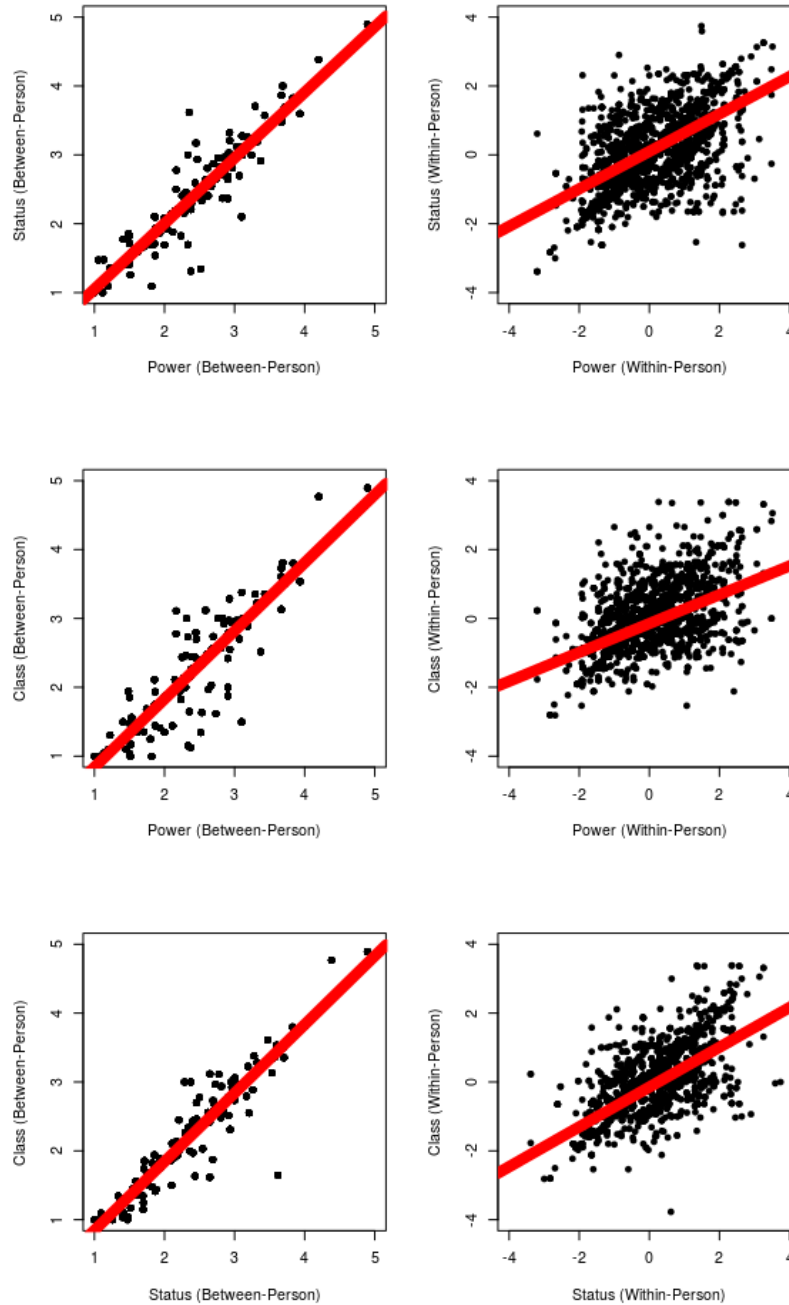


Figure 7. Relationships between power, status, and class at between-person level (left panels) and within-person level (right panels).

As predicted, I found greater divergence at the within-person level

than at the between-person level across all three pairwise relationships. For example, the relationship between social class and power was much stronger at the between-person level ($\beta = .69$, 95%CI = [.60, .79]) than at the within-person level ($\beta = .34$, 95%CI = [.31, .37]). Almost 50% of the variance in a person's average level of social class is explained by the person's average level of social power - over four times the amount of shared variance at the within-person level (12%).

Hypothesis 3: Dimensions of Social Hierarchy Will Have Different Situational Antecedents

To test whether within-person variation in social power, status, and class would be explained by variation in the kinds of situations that participants reported being in, I again tested a series of multilevel regression models that predicted each domain of social hierarchy as a function of what participants were doing and the number of other people with whom participants were interacting. Because there were moderate to strong relationships between these different dimensions, I calculated residual scores for each domain of social hierarchy that remove the effects of the other relationships. Tests of these linear models suggest that assumptions of normality and heteroscedascity were not violated. These residual scores are plotted as histograms in Figure 8.

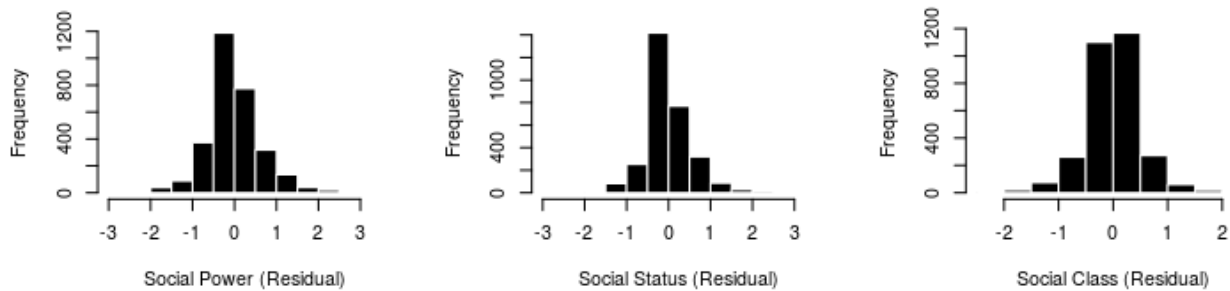


Figure 8. Histogram of residual scores for unique effects of social power, status, and class.

As expected, I found that what participants were doing explained a significant amount of within-person variation in social power ($\chi^2 = 100.1$, $df = 26$, $p < .01$), as well as social status ($\chi^2 = 106.8$, $df = 26$, $p < .01$). In contrast, less within-person variation in social class was explained by what participants were doing ($\chi^2 = 39.6$, $df = 26$, $p = .04$), suggesting that people's ratings of what they were doing were less influential to ratings of social class than ratings of social power or status.

These effects are illustrated in Figure 9 for social class (light gray), power (dark gray), and status (medium gray). Each bar represents the predicted value of the residual score of a hierarchical domain compared to the average of that domain across five specific situations. Error bars represent 95% Confidence Intervals for each effect, calculated using bootstrapping. For example, when people report using online social networks (e.g., Facebook) they report feeling significantly higher in social power than they tend to feel on average, significantly lower in social class than they do on average, and do not feel any different in social status than they do on average. In contrast, when participants report that they are relaxing, they report being significantly lower in social power and status, but significantly higher in social class.

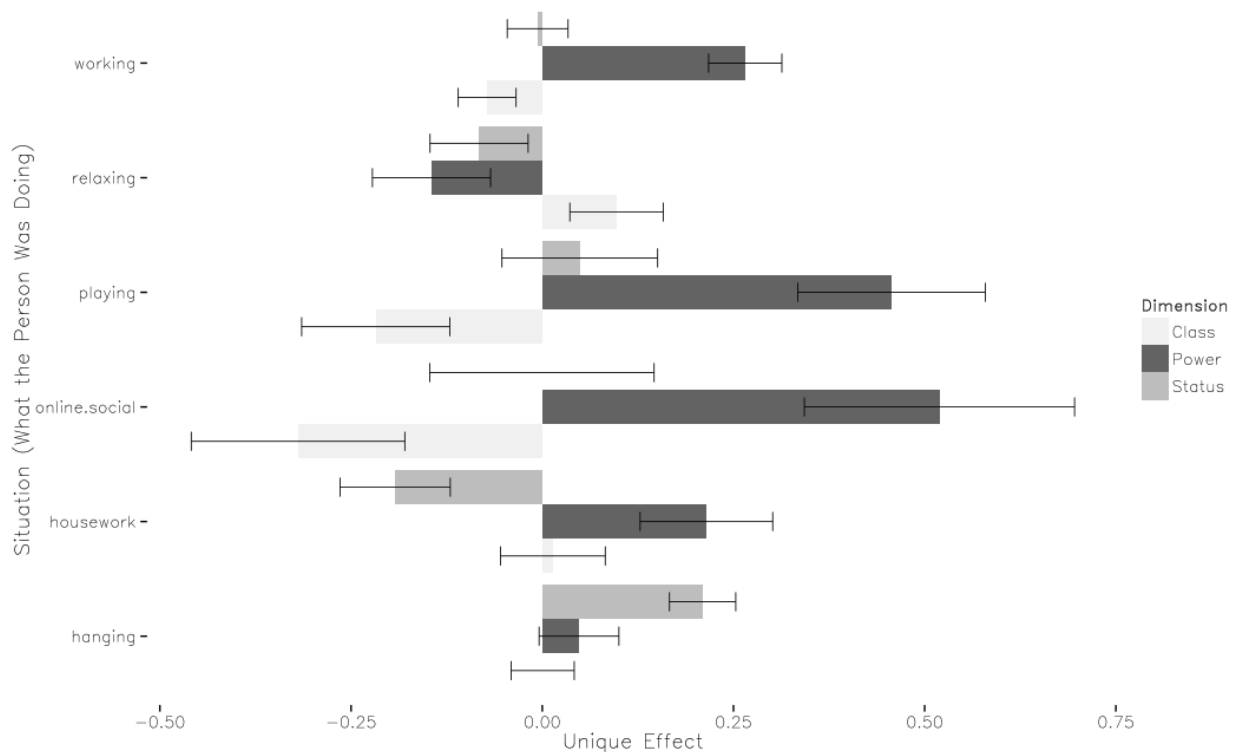


Figure 9. Unique effects of social power, status, and class across six different activities.

I also found that whereas the number of other people participants were directly interacting with explained a significant and substantial percentage of variance in social status ($\chi^2 = 183.1$, $df = 7$, $p < .01$), the number of other people explained less variance in social power ($\chi^2 = 17.4$, $df = 7$, $p = .02$) and social class ($\chi^2 = 13.4$, $df = 7$, $p = .06$). Together,

these findings suggest that in real-life contexts, social status is more influenced by others than social power or class.

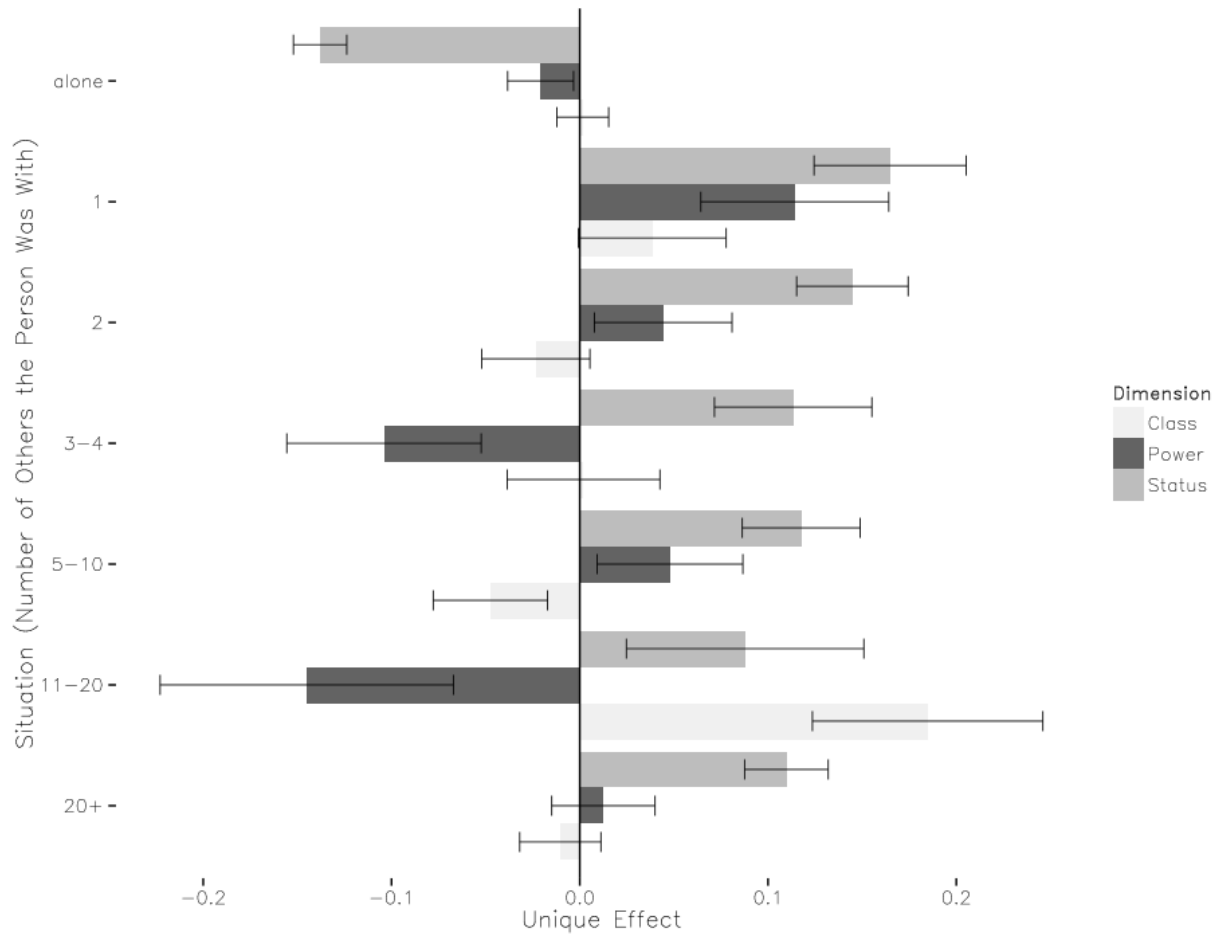


Figure 10. Unique effects of social power, status, and class across different social interactions.

These effects are illustrated in Figure 10. Whereas people report feeling low in status when alone than they do on average, they report feeling higher in status than on average when with other people. In contrast, the unique effects of power and class demonstrate that people are less sensitivity to the number of others in the situation for these dimensions of social hierarchy.

Hypothesis 4: Dimensions of Social Hierarchy Hold Different Consequences

Finally, I tested the prediction that changes in a social class - the more stable dimension of social hierarchy - would cause changes in social power and status - the less stable dimensions of social hierarchy.

To test this hypothesis, I conducted a series of lagged hierarchical regression analyses (Duckworth Tuskayama, & May, 2010), predicting one domain of social hierarchy (i.e., social power) at Time N+1 from all three domains of social hierarchy (i.e., social status and class) at Time N.

The results of these lagged analyses are reported in Table 1. The bold fixed effects estimates on the diagonal represent the test-retest reliability for each of the three hierarchical domains. Social hierarchy at Time N was positively related to social hierarchy at Time N+1 for social power ($\beta = .09$, 95%CI = [.04, .14]), social status ($\beta = .05$, 95%CI = [.00, .11]), and social class ($\beta = .18$, 95%CI = [.13, .23]). That social class exhibited the greatest test-retest effect compared to power or status is consistent with its relatively lesser amount of within-person variation.

Table 1.

Predicting Residual Lagged (N+1) Ratings of Power, Status, and Class from Previous (N) Ratings of Power, Status, and Class, Controlling for Time of Assessment.

	Time N+1 (Lagged) Predictor Variables		
	<i>Power</i>	<i>Status</i>	<i>Class</i>
Time N Random Effects			
<i>Participant</i>	.19	.25	.35
<i>Residual</i>	.68	.61	.48
Time N Fixed Effects			
<i>Intercept</i>	.02	.02	.02
<i>Social Hierarchy Domain</i>			
<i>Power</i>	.09 **	.03	.02
<i>Status</i>	-.01	.05 *	-.01
<i>Class</i>	.13 **	.13 **	.18 **
<i>Time of Assessment</i>	-.01	.01	.01
Model Fit			
<i>Deviance</i>	6685	6438	5863

Note. * $p < .05$; ** $p < .01$

Critically, I also found support for my prediction that the relationship between changes in domains of social hierarchy would be asymmetrical. Ratings of social class at one time point predict significant *changes* in subsequent ratings of social power ($\beta = .13$, 95%CI = [.07, .19]), and social status ($\beta = .13$, 95%CI = [.07, .18]). However, neither changes in social power nor social status predict changes in other

domains of social hierarchy at later time points (average $\beta = .02$).

General Discussion

This chapter contributes to research on social hierarchy in three ways. First, these results provide new empirical evidence that differentiates social power, status, and class from each other. Second, these findings outline several ways that a within-person approach can advance researchers' understanding of social hierarchy. Third, there are several limitations to the within-person approach used in this chapter that identify new opportunities for future research.

Differentiating Dimensions of Social Hierarchy

I found replicating evidence across two experience sampling studies that related dimensions of social hierarchy can be differentiated at the within-person level. Below, I summarize key results from this chapter, organized for each of the three dimensions of social hierarchy I studied.

Social power. These results suggest that the majority of variance in social power is characterized by substantial within-person variation. People's subjective feelings of how much influence and control they can exert change as a function of what the person is doing, and to a lesser extent who the person is with. However I also found evidence for individual differences in social power - between-person variance explained a significant (but small) percentage of total variance, and a person's social power at one time point was positively related to the person's social power at a second time point. Social power at one time point was not related to either social status or social class at later time points.

Social status. Like social power, the majority of variance in social status was described by within-person variation. Like social power, I found evidence for stable individual differences in social status, both in terms of explained between-person variance and test-retest reliability. Like social power, changes in social status do not cause people to change in other dimensions of social hierarchy at a later time point. What appears to differentiate social status most from other dimensions of social hierarchy is that more variance in social status is explained by who people are with than what people are doing. This suggests that researchers interested in the effects of social status might focus on specific features of relationships, such as the duration or kind of relationship.

Social class. Unlike social power and status, stable individual differences explained the majority of variance in social class. This does not mean that social class is invariant within-persons; however people's

perceptions of their own social class change from situation to situation significantly less than their perceptions of social power. Consistent with this idea, ratings of what the person was doing or the number of other people the person was with were weak predictors of variation in social class.

Implications for Research on Social Hierarchy

Together, these findings demonstrate the utility that examining within-person processes can hold for researchers interested in social hierarchy.

Overlap in power, status, and class. In real-life situations, dimensions of social hierarchy are characterized by considerable overlap. Even at the within-person level where they showed the most amount of divergence, social power, status, and class were strongly related to each other. Researchers seeking to make claims about processes related to one dimension should therefore include measures of multiple constructs in their studies, and control for this shared variance. In this chapter, for example, I found evidence that the unique effects of social status, but not social power or class, was related to variation in people's social interactions.

Although my results empirically demonstrate that dimensions of social hierarchy are highly related at the level of the situation, that power, status, and class are *less* related within-persons than between-persons suggests that researchers seeking to understand the ways in which hierarchical dimensions are different from another might examine specific social contexts rather than focus on broad individual difference measures. Past work is supportive of this point; conceptual definitions and experimental research that highlights differences between power and status often evoke certain roles or situations (e.g., Keltner, Gruenfeld, & Anderson, 2003; Fragale, Overbeck & Neal, 2011; Dubois, Rucker, & Galinsky, 2015).

The "trickle down" effects of social class. Furthermore, these findings provide another way to think about the differences between social power and class. Whereas Dubois, Rucker, and Galinsky (2015) demonstrate that manipulations of power lead to the same effects as manipulations of social class (Piff et al., 2009), in this chapter I found that social class predicts subsequent changes in social power. My findings suggest that one reason why social class and power appear to hold similar effects is that manipulations and measures of class will correspond to similar manipulations and measures of social power. That is, Piff et al. (2009)

may have found that changes in social class lead to more self-interested behaviors because those changes in class "trickle down" to social power.

Future research could examine this "trickle down" effects of changes in social class further. For example, will manipulations of social class correspond to stronger changes in social power than will manipulations of social power on social class? Will interventions that help people feel higher in social class be more effective than interventions focused on helping people feel higher in social power?

Limitations and Future Research Directions

Methodological limitations. This contextualized approach to social hierarchy is only as good as its method, and several methodological limitations bear mention. First, experience sampling methods are difficult to collect (e.g., Conner, Tenne, Fleeson, & Barrett, 2009). Thus, sample sizes for studies using these methods average around 40 (e.g., Fleeson & Gallagher, 2009). Although I replicated findings across two samples, these samples were drawn from the same population. It is possible that these effects might vary in other samples. Future research should examine if differences in culture, age, personality, and demographic background shape the way that people vary in hierarchical dimensions across everyday life.

Another limitation of this research is I used single-item measures of power, status, and class. This decision was based on the intensive repeated-measure design required for experience sampling methods, and past research that suggests single-item measures can adequately represent psychological processes (Gosling, Rentfrow, & Swan, 2003; Robins, Hendin, & Trzesniewski, 2001). However, single-item measures limit the scope of these results in three ways.

First, it is not possible to estimate measurement reliability with single-measures of social hierarchy. In this chapter, I was more concerned with comparing the three dimensions of social hierarchy to each other than perfectly estimating the degree of within-person variation. However, the use of single-item measures makes it difficult to determine the extent to which within-person variation is influenced by error. Although there is no reason to suspect that measurement error would influence one dimension of social hierarchy more or less than the others, future research should assess the three dimensions of social hierarchy with multiple indicators.

Second, it is possible that the greater divergence at the within-person level (i.e., Hypothesis 2) is due to the principle of aggregation. Between-person effects are estimated based on multiple ratings (up to 36), and are thus more reliable than within-person effects, which are estimated

based on single ratings. The smaller correlational relationship at the within-person level may partially or entirely be due to error, and not to any meaningful difference between the two levels of analysis.

Third, the single-item measures were all positively keyed; participants rated the extent to which they were *high* in power, status, and class. It's unclear if there would be different patterns of results if participants rated the extent to which they were *low* in power, status, and class.

To address these methodological limitations, future research should examine other methods of within-person assessment. For example, the "day reconstruction method" (Kahneman et al., 2004) estimates within-person variation by having participants answer questions about their thoughts, feelings, and behavior in the previous day. Though this method does not allow researchers to examine patterns of variance across multiple days, it is less intensive for individual participants. Researchers could therefore include multiple items for each dimension of social hierarchy and recruit more participants.

Conceptual limitations. Like all experience sampling research, these studies rely on self-report methods of assessment. Although past research has demonstrated ways in which self-reports of social hierarchy are relevant to objective measures of status and rank (Anderson et al., 2001; Kraus et al., 2012), future research might determine whether these patterns extend to methods that do not depend on self-report methods. For example, would people's ratings of others' hierarchy (e.g., Catterton, Carney, Chen, John, & Naumann, *under review*) show divergent patterns of within-person variation? Would peers' evaluations of participants vary across real-life situations?

Summary and Conclusion

In this chapter, I developed a *within-person* approach to social hierarchy that accounts for the way in which social power, status, and class vary across a person's everyday life experiences. Together, these findings suggest that power, status, and class differ in terms of their within-person variance (Hypothesis 1), are more differentiated at the within-person level than at the between-person level (Hypothesis 2), hold unique situational antecedents (Hypothesis 3), and are associated with asymmetrical outcomes (Hypothesis 4).

Chapter 3: The How, When, and Why of Situational Suppression Use

Summary

One paradox in the emotion regulation literature is why people continue to use a maladaptive emotion regulation strategy when less costly strategies exist. Whereas past research has examined the use of emotion regulation strategies in terms of broad individual differences or responses to controlled lab experiments, the current study takes a naturalistic and repeated-measures approach to examine the use of expressive suppression in real-life situations. Using an experience sampling design, I find evidence across two independent samples (total $N = 192$) that (1) there is considerable within-person variation in suppression use, (2) that the *situational* use of suppression is explained both by stable individual differences and situational differences in social power and status, and (3) that suppression use does not appear to be related to reduced well-being when used in contexts in which people report feeling low in social power. Together, these findings bridge functionalist theories of emotion with the emerging literature on emotion regulation, and demonstrate the benefits of studying emotion processes in the kinds of situations in which they are used.

The How, When, and Why of Situational Suppression Use

As anyone who has felt sad at a friend's birthday party, nervous when trying to impress a first date, or proud about an accomplishment others failed to achieve knows, there are many situations in which expressing one's internal states to others might interfere with short- or long-term goals. People are not passive victims to their emotions, but instead utilize a broad range of *emotion regulation* strategies to modulate the experience or expression of emotion (Gross, 1998b, 2002; Gross & Thompson, 2007; Tamir, 2011).

A considerable body of empirical research has outlined the specific intra- and interpersonal consequences that are associated with each of these emotion regulation strategies. Yet to date, no research has examined how people regulate their emotions in the kinds of specific situations that they encounter in their everyday lives. In this chapter, I seek to examine how people vary in their use of emotion regulation in daily life, test hypotheses about certain features of persons and situations that are likely to predict the use of emotion regulation, and discuss the consequences of this situational emotion regulation.

Emotions and Situations

Emotion scholars have long-recognized the important role that situations have in shaping emotion experience, expression, and social functions. Darwin (1872) theorized that the physical expressions we now associate with various emotional states (e.g., anger) originally served specific anatomical functions (e.g., flattened ears, bared teeth) that helped individuals survive specific situations, and thus improved our evolutionary ancestors' chances of passing their genes on to the next generation. More recently, scholars across research traditions have considered emotions as a coordinated response to specific situations (Frijda, 1986; Gross, 1998a; Gross & Thompson 2007; Lazarus, 1991). For example, the "modal model of emotion" (Barrett, Ochsner, & Gross, 2007; Gross, 1998b) places situations at the beginning of the emotional response process.

Other researchers emphasize that the objective features of a situation are less important to the elicitation of an emotion than the person's subjective *appraisal* of that situation (Caspi & Roberts, 2001; Ellsworth, 1994; Fridja, 1988; Smith & Ellsworth, 1985; Smith & Lazarus, 1993). In their work, Smith and Ellsworth (1985) found evidence that six

dimensions characterize people's interpretations of situations, and that these interpretations can differentiate emotions. Other researchers describe ways in which the same situation can be considered in ways that give rise to different emotional responses (e.g., Caspi & Roberts, 2001; Folkman & Lazarus, 1985; McCrae, 1984). For example, whether a person perceives him or herself as having control in a situation can differentiate emotions such as sadness and anger (Smith & Ellsworth, 1985; Tiedens, 2001).

Emotions can also serve important social functions by signaling a person's internal states to others (e.g., Frijda & Mesquita, 1994; Gross & Thompson, 2007; Keltner & Gross, 1999; Keltner & Haidt, 1999; Keltner & Kring, 1998). Social functionalist accounts suggest that even negative emotions can serve adaptive social functions when used in certain situations (Keltner & Gross, 1999). For example, expressions of sadness signal that a person is in need of help, and thus increase the chance that others will provide help (Graham, Huang, Clark, & Hegelson, 2008), embarrassment can help a person who has violated some social norm appease more powerful others by signaling deference (Keltner & Buswell, 1997; Keltner & Haidt, 1999), and anger can improve performance on competitive tasks (Tamir, Mitchell, & Gross, 2008). Together, such research not only demonstrates that emotions can hold important social functions, but suggests that the utility of an emotion depends on the situation (or appraisal of the situation) in which it is expressed.

Emotion Regulation

Though the literature referenced above defines emotions in part by features of the situation, Gross' (1998b) influential process model defines emotion regulation by features of the emotional response that each regulation strategy targets. *Cognitive reappraisal* is an *antecedent-focused* strategy that operates before an emotion is fully generated, and works to change some aspect of the person's *appraisal* of the situation that triggers the emotional response (Gross, 1998a). For example, the same situation (e.g., sitting in traffic on the I-580) can be interpreted in ways that give rise to frustration (e.g. "I'm wasting my life in traffic") or in ways that give rise to less intense negative emotions (e.g., "This is an interesting opportunity to observe other people.") By changing what an individual experiences internally, cognitive reappraisal subsequently regulates the overt expression of an emotion (Gross & Thompson, 2007).

In contrast, *expressive suppression* refers to a response-focused

regulation strategy that targets only the behavioral component of an emotion. Individuals who engage in suppression attempt to reduce the overt expression of an emotion, but do nothing to change the events or appraisals of situations that give rise to the experience of emotion (Gross, 1998b; Gross & John, 2003; Gross & Levenson, 1997). For example, a person who uses suppression to hide her or his visible display of anger while stuck on the I-580 would still feel anger on the inside.

Past research has focused on how these two emotion regulation strategies differ in terms of their consequences for the experience and expression of emotion, well-being, and social functioning. Although suppression does little to reduce the internal experience of an emotion, it is more effective than reappraisal at reducing the outward expression of emotion (Gross, 1998a). Researchers thus consider suppression to be the emotion regulation strategy that is most directly relevant to a person's social goals because it interferes directly with the component of an emotion that signals a person's internal states to others (Campos, Walle, Dahl, & Main, 2011; McRae, Heller, John, & Gross, 2011; Nezlek & Kuppens, 2008; Russell, Bachorowski, & Fernandez-Dols, 2003).

It is somewhat ironic, then, that this other-oriented emotion regulation strategy is associated with a wide range of *negative* social outcomes. Evidence from both lab-based interactions and studies of naturally occurring relationships suggests suppression is associated with decreased social support, relationship closeness, social warmth, and relationship satisfaction among participants and those they interact with (Butler et al., 2003; English & John, 2013; English, John, Srivastava, & Gross, 2012; Gross & John, 2003; Impett et al., 2012; Srivastava, Tamir, McGonigal, John, & Gross, 2009). Reappraisal, on the other hand, is considered by many to be the golden child of the emotion regulation family, as it is not only associated with various positive well-being and social outcomes (English & John, 2013; Gross & John, 2003; John & Gross, 2004; Srivastava, Tamir, McGonigal, John, & Gross, 2009), but also requires less cognitive effort than suppression (Richards, Butler, & Gross, 2003; Richards & Gross, 1999).

The Paradox of Suppression

Such research reveals a paradox inherent to the use of suppression: why do people use a maladaptive emotion regulation strategy when other less costly strategies exist? To address this question, I extend social functionalist accounts of emotion to the study of emotion regulation. In

contrast to past research that focuses on individual differences in the *stable* use of reappraisal and suppression, I focus on individual differences in the *situational* use of suppression. Below, I develop three research questions that guide this research, and examine how, when, and why people might use suppression across real-life situations.

Question 1: Do People Vary in the Use Suppression Across Real-Life Situations?

To address the question of *why* people use suppression, it's important to first consider *how* people use suppression. However, of the 500-plus articles that have been published on emotion regulation since 2001, only 12% measured emotion regulation in the context of an actual social interaction (Campos et al., 2011). This discrepancy between the situations researchers study and the contexts in which emotion regulation actually takes place is problematic, since it means researchers may not fully understand how suppression use operates in real life.

A few researchers have begun to examine the situational use of emotion regulation by examining changes in the use of suppression in response to *specific* situations. For example, Srivastava et al. (2009) found that suppression use increased when students transitioned from high school to a new college environment. Similarly, McRae et al. (2011) found that participants reported using suppression less at the counter-culture art festival Burning Man than when they are in their regular home environment.

Other researchers have examined change in emotion regulation by measuring daily variation in suppression and reappraisal use. For example, Nezlek and Kuppens (2008) measured suppression once each day over the course of the week, and report that participants differed as much from themselves in their use of suppression over the course of the week as they differed from each other. Le and Impett (2013) assessed daily variation over the course of two weeks, but did not report the extent to which people differed from their own average or from each other in their use of suppression.

These studies provide preliminary evidence that emotion regulation is not entirely stable. However, by averaging across situations with daily measures (e.g., Le & Impett, 2013; Nezlek & Kuppens, 2008) or examining the use of suppression in response to one situation (e.g., McRae et al., 2011; Srivastava et al., 2009), past research is not able to examine how people vary in suppression use as a response to different real-life

situations. It is thus unclear whether suppression use is best characterized by stable individual differences or by variability across situations.

On the basis of past individual difference research (e.g., Gross & John, 2003; Nezlek & Kuppens, 2008; Srivastava et al., 2009), I expect to find significant *between-person* differences that characterize the stable use of suppression. However, I also expect to find substantial *within-person* variation in suppression use that characterizes situational suppression use (*Hypothesis 1*). Between-person and within-person differences are conceptually and statistically distinct (Robinson, 1950; Snijders, 2001). Thus, people should differ from each other in their average use of suppression (i.e., there should be differences in the stable use of suppression), and people should vary from their own average use of suppression across different situations (i.e., there should be differences in the situational use of suppression).

Furthermore, I predict that there will be greater within-person variance in the use of suppression than reappraisal. As a response-focused emotion regulation strategy, suppression use occurs after an emotion has been elicited and should vary according to the different situations that a person finds her or himself inhabiting. Thus, someone who uses suppression in one situation may or may not use suppression in another situation. In contrast, reappraisal is an antecedent-focused strategy that occurs early in the regulatory process, and is related to individual differences in a person's general cognitive style (John & Gross, 2004; Gross & Thompson, 2007). Someone who uses reappraisal in one situation should therefore be more likely to use reappraisal in another situation than someone who tends not to use reappraisal.

Question 2: When Do People Use Suppression?

Though past theory and research emphasize the ways in which emotion and emotion regulatory processes serve as responses to situations (Barrett & Campos, 1987; Erber, Wegner, & Therriault, 1996; Gross, Jakobs, Manstead, & Fischer, 1999; Gross, Richards, & John, 2006; Tamir et al., 2008; Tamir, 2009), few studies examine the specific social context in which regulation occurs. Individual difference approaches to emotion regulation tend to aggregate across situations (e.g., Gross & John, 2003; Le & Impett, 2013; Nezlek & Kuppens, 2008), whereas experimental approaches typically manipulate emotion regulation strategy participants are asked to use, and not the feature of the situation or the emotion that

is the target of regulation (e.g., Butler et al., 2003; Gross & Levenson, 1993). Measuring emotion regulation at the level of the situation allows researchers to not only distinguish the stable and situational sources of emotion regulation, but also to determine what features of situations and persons explain when people use more or less suppression at both levels of analysis.

Features of situations. One general feature of situations that has received the some attention in the literature is whether or not people regulate their emotions in social or non-social situations. Gross, Richards, and John (2006) report that of the 19 participants who described using suppression when asked, 98% of these responses involved a social interaction. Such findings are cited to suggest that suppression use is more likely to occur in social interactions (e.g., Campos et al., 2011; English, John, Srivastava, & Gross, 2012). However, it is unclear whether these results mean that people don't suppress their emotions when alone, or whether people tend to recall social interactions when asked to describe situations in which they suppressed emotions to psychologists. If someone stubs her toe in the middle of a forest and does not shout in pain, does she still suppress?

I predict that people would be more likely to report using suppression in social situations than in non-social situations (*Hypothesis 2A*). Based on past theory that suppression use is an response-focused strategy, I also expected that a significant percentage of variance in suppression use would be explained by differences in the situations that people inhabited. However, I did not hold specific predictions about which situations or emotions would lead people to suppress.

Features of Persons. Appraisal theory suggests that the specific features of a situation may be less relevant to the use of suppression than the way in which the person construes or responds to the situation that she or he inhabits (e.g., Ellsworth, 1994; Fridja, 1988; Smith & Lazarus, 1993). People often react to the same situation in ways consistent with underlying dispositional tendencies (e.g., Caspi & Roberts, 2001; McCrae, 1984). For example, at a party one person might actively avoid any social contact while another person is simultaneously pouring drinks, holding two conversations, and motioning toward others to get dancing. In this situation, a person's feeling of extraversion or introversion would likely explain these different patterns of behavior.

Past research on individual differences in emotion regulation point

to a variety of personality dimensions that are related to the stable use of suppression (e.g., Gross & John, 2003; John & Gross, 2004; English & John, 2013). For example, individual differences in extraversion not only explain the greatest percentage of variance in personality (John & Srivastava, 1999), but also appear to be one of the strongest predictors of stable suppression use (Gross & John, 2003).

Hierarchical states such as social power and status are other important psychological dimensions that define many situations and are related to a variety of consequences for a person's behavior and emotion (French & Raven, 1959/1986; Keltner, Gruenfeld, & Anderson, 2003; Chapter 2 of this dissertation). For example, people measured or manipulated to be high in social power are more likely to express their emotions and behave in disinhibited ways than people low in social power (e.g., Anderson & Berdahl, 2002; Anderson & Galinsky, 2006), which suggests that they may be less likely to suppress their emotions. Indeed, English & John (2012) found that people who use suppression report being lower in status than people who do not use suppression.

However, just because past research suggests that individual differences in extraversion and social power are related to the stable use of suppression does not necessarily mean that these same personality differences will predict the *situational* use of suppression. In the same way suppression use can be distinguished between its stable and situational components, past research by Fleeson (2001/2007) distinguishes between the stable components of personality (described by between-person effects) and the situational components of personality (described by within-person effects). Relationships between constructs such as personality and suppression at the level of individual differences are conceptually and statistically independent of relationships at the level of specific situations (Robinson, 1950).

I predict that suppression use will be influenced by both between-person and within-person differences in personality (*Hypothesis 2B*). I expect to replicate past research and demonstrate that people who are high in extraversion and low in social power on average will suppress more on average (English & John, 2013; Gross & John, 2003). However, I also predict that situation-specific differences in personality will predict the situational use of suppression above and beyond these individual difference measures. Specifically, I expect that whereas people will use situational suppression more in situations where they feel relatively more

extraverted than their own average, people will use situational suppression less in situations where they feel relatively low in social power than they do on average.

Question 3: Why Do People Use Suppression?

Past research and theory on emotion regulation maintain that suppression holds negative social consequences because it interferes with the emotion generation process and lead to an incongruence between how people feel and what they express (English & John, 2013). For example, Butler et al. (2003) found that observers report less closeness to others who suppress their emotions during a negative film clip, Srivastava et al. (2009) reported that people who suppressed their emotions in the transition to college reported reduced social satisfaction, Nezlek & Kuppens (2008) found that suppression use over the course of a week was related to negative emotional and well-being states, and Schlatter & Cameron (2010) found that women who used more suppression during chemotherapy treatments reported poorer coping and more negative symptoms.

However, social functionalist accounts of emotion don't claim that emotion expressions are *always* good, but instead that it's important to consider the consequences of emotion in the social context in which it is expressed (Gruber, Mauss, & Tamir, 2013; Keltner & Kring, 1998). In the same way that negative emotions such as embarrassment and anger can hold adaptive benefits in certain situations (Keltner & Buswell, 1997; Tamir et al., 2008), the use of suppression in certain situations might hold positive outcomes. This approach suggests that though the stable use of suppression may hold maladaptive functions (e.g., English & John, 2013; Gross & John, 2003), the use of suppression in specific situations may be less maladaptive.

Several studies are supportive of this functionalist account of suppression. Bonanno, Papa, Lalande, Westphal, and Coifman (2004) found that NYU students' ability to successfully engage in suppression when directed to in a prior laboratory session predicted greater psychological adjustment in the year of the September 11th terrorist attacks on the World Trade Center. More recently, Le & Impett (2013) found that individuals who see themselves as interconnected (e.g., Markus & Kitayama, 1991) exhibited increases in personal well-being (measured as the difference between positive and negative emotion) and relationship satisfaction on days in which they reported suppressing their emotions and making a sacrifice for their romantic partner.

These findings suggest that there will be certain situations in which the situational use of suppression is adaptive. That is, the consequences associated with situational suppression use should depend on features of the situation or emotion that suppression is regulating. However, one challenge in testing this prediction is that there are a wide variety of possible situations in which suppression use might be employed. Rather than try to account for different patterns of outcomes across these different situations, or focus on one specific situation (e.g., Srivastava et al., 2009), I examine one general feature of situations that has far-reaching effects on a person's cognition, affect, and behavior: social power.

Past research demonstrates that differences in people's access to social resources such as power, status, and class are related to differences in people's ability to exert influence over their environment in order to obtain rewards (Keltner, Gruenfeld, & Anderson, 2003), make them less dependent on others (Piff, Kraus, & Keltner, 2012) and more likely to express their true opinions (e.g., Anderson & Berdahl, 2002; Chen, Langner, & Mendoza-Denton, 2009; Chen, Lee-Chai, & Bargh, 2001; Kraus, Chen, & Keltner, 2011). Thus, the use of suppression would be contrary to social norms regarding the expression of desires and interests for people high in social power. In contrast, suppression use would be consistent for those norms for people low in social power.

I therefore predict that social power will serve as one feature of situations that explains when suppression is associated with positive or negative consequences (*Hypothesis 3*). Specifically, I expect that suppression use will be less maladaptive for people who tend to be low in social power (i.e., low stable social power), as well as in situations where people find themselves lower in social power than they find themselves to be on average (i.e., low situational social power).

The Current Research

In Table 2, I summarize the predictions derived from questions about how, when, and why people use suppression in everyday life. To test these predictions, I designed an experience sampling survey for participants to answer questions about objective features of their situation, as well as their personality and use of emotion regulation in that situation. Unlike past research, this method allows me to examine the behaviors, antecedents, and consequences of suppression use in everyday life.

Table 2.
Summary of Chapter 3 Hypotheses.

Prediction		Support?	
<i>Question 1: Do people vary in their use of suppression?</i>		<i>Sample 1</i>	<i>Sample 2</i>
Hypothesis 1	There will be substantial between- and within-person variation in suppression use.	<i>yes</i>	<i>yes</i>
<i>Question 2: When do people vary?</i>			
Hypothesis 2A	Suppression use varies as a function of the situation: the sociality of the situation, the emotions participants experience, and the situations participants inhabit.	<i>yes</i>	<i>yes</i>
Hypothesis 2B	Suppression use varies as a function of the person: situation-specific levels of extraversion and social power .	<i>mixed</i>	<i>mixed</i>
<i>Question 3: Why do people vary?</i>			
Hypothesis 3	Suppression use holds different consequences for well-being depending on the person's level of social power.	<i>yes</i>	<i>mixed</i>

To ensure the reliability of these findings, I employed this experience sampling procedure across two samples. Below, I describe the methods for these two samples; results will be reported for each sample.

Methods

Participants

Participants were recruited from a large public university on the West Coast. In Sample 1, 77 participants signed up for the study; in Sample 2 164 participants signed up for the study. To be included in the study, participants needed to complete at least 40% of the surveys, take longer than 20 seconds to complete the survey, and have non-zero variance in their ratings.

Sample 1 included 57 participants (89% Female; 50% Asian, 31% White, 9% Latino, 4% Middle Eastern, 2% Black, 4% Other), whereas Sample 2 included 137 participants (64% Female; 53% Asian, 25% White, 11% Latino, 7% Middle Eastern, 1% Black, 3% Other). Three participants in Sample 1 did

not provide demographic information.

Procedures

Experience sampling procedures were identical across the two samples. Participants were sent text messages via smartphone six times a day for six days. Surveys in both samples were administered on a fixed schedule, and sent at 10:00, 12:00, 14:00, 16:00, 18:00, and 20:00. In Sample 1, the median completion rate after filtering was 78.2%; in Sample 2 it was 86.1%. The median completion time for each experience sampling survey in Sample 1 was 96 seconds; the median survey completion time was 67.9 seconds in Sample 2 (The longer completion time in Sample 1 was likely due to the presence of additional items. These items were unrelated to any of the independent or dependent variables reported in this study; see Appendix for a full list of items used.)

Measures

Each text message directed participants to an online survey, in which they were asked to answer questions about various features of their situation, personality, and behavior in the last thirty minutes.

Features of the Situations. Participants were asked to describe what they were doing before taking the survey by selecting from a list of different activities and situations. This list was based on previous experience sampling research (Kahneman et al., 2004; Killingsworth & Gilbert, 2010), and included situations relevant to students such as "browsing the internet", "reading", "relaxing, doing nothing", "studying", and "talking, conversation".

Participants were also asked in both samples to describe "How many other people were you directly interacting with in this situation?" Participants selected from one of seven response options: "0 (I was alone)", "1", "2", "3-4", "5-10", "11-20", and "20+".

Features of the Person. Participants were then asked to make ratings of their personality, based on the situation they described. All ratings were made on a Likert scale from 1 (*Not at All*) to 5 (*Very Much*), and followed the question stem, "In this situation..."

Extraversion. In Sample 1, participants rated the extent to which they were "Extraverted, enthusiastic" and were "Reserved, Quiet" (reverse scored). These two extraversion items ($r = .62$) were selected from the Ten Item Personality Inventory (Gosling, Rentfrow, & Swan, 2003), and were combined to form a composite extraversion item. In Sample 2, I assessed extraversion with the single item "I was outgoing, sociable".

Social Power. In Sample 1, I assessed social power by asking participants to rate the extent to which they "Had a lot of power (e.g., can exert influence)", "Had a lot of status (e.g., is respected by others)", and "Had a lot of class (e.g., has high rank in society)". In Sample 2, I assessed social capital by asking participants to rate the extent to which they "Had a lot of power (e.g., can exert influence)" and "Had a lot of status (e.g., is respected by others)". Because these items were highly related (Sample 1 $\alpha = .89$; Sample 2 $r = .87$) and differences between power, status, and class were not the focus of this study, I combined these constructs into a single item. Effects replicated across all three measures.

Emotion Regulation. In both samples, I measured situational emotion regulation use by adapting items from the Emotion Regulation Questionnaire (Gross & John, 2003). To assess suppression use, participants rated the extent to which "I controlled my emotions by keeping them to myself." In Sample 1, I also assessed reappraisal with the item, "I controlled my emotions by changing the way I thought about the situation I was in." Reappraisal use was not measured in Sample 2.

Well-Being. I assessed participant well-being with a measure of self-esteem ("I had high self-esteem") and positivity "How did you feel in this situation". In Sample 1, the self-esteem measure ranged from 1 (*Not at All*) to 5 (*Very Much*), whereas the positivity measure used a scale from 0 (*Bad*) to 10 (*Good*), whereas Sample 2 used a scale from 0 (*very negative*) to 10 (*very positive*). These items were positively correlated ($r = .49$ in Sample 1, $r = .51$ in Sample 2) and were combined to form a single index of well-being. Effects replicated for both self-esteem and positivity when analyzed separately.

Estimating Stable and Situational Effects

To distinguish between the stable and situational components of psychological phenomena, I calculated two scores for each construct that represent the between-person and within-person level of analysis. To describe the between-person level of analysis, I calculated an average score for each participant that describes his or her stable pattern of response across the different situations. This stable measure did not vary across the different situations; each person had one average score for each construct. A participant with a high between-person effect for suppression would tend to use suppression across all situations.

To describe the within-person level, I subtracted each participant's

rating made during the experience sampling assessment from her or his average rating across the different situations (i.e., the between-person effect calculated above). This mean-centered variable describes whether the person was above or below his own mean for each situation. Unlike the between-person effect, this variable did vary across the different situations. A participant with a positive within-person effect for suppression would be someone who used suppression more in that situation than they did on average across all the situations they rated.

Means, standard deviations, ranges, and zero-order correlations between all variables, including those not reported in the methods section of this chapter, are reported in the Appendix.

Results

Question 1: How Do People Use Suppression in Real-Life Situations?

Hypothesis 1: Suppression use is situational. To test the first hypothesis that there would be substantial within-person variation in the use of suppression, I used multilevel modeling (Snijders, 2011) to predict suppression use from a random intercept that varied between-persons. This random intercept model estimates the fixed intercept effect (i.e., what the average person's suppression was like), a random intercept for each participant that describes the amount of variation due to people being different (i.e., between-person variance), as well as an error term that describes the amount of variation not explained by between-person differences (i.e., within-person variation).

As seen in Table 3, there was substantial between-person variance in suppression use; individual differences accounted for 26.7 percent of total variation in Sample 1, and 35 percent of variation in suppression use in Sample 2. The 95% Confidence Intervals for these effects do not include zero, and suggest that these variance estimates are significant. These results support past research that there are differences in people's stable use of suppression across situations (e.g., English & John, 2013; Gross & John, 2003).

However, there was also substantial within-person variation in suppression use. In fact, in both Sample 1 and Sample 2 the majority of variance in how people use suppression was not explained by stable individual differences. Instead, there was considerable variance in how people used suppression across situations.

Table 3.

Variance in Emotion Regulation Explained by Between- and Within-Person Differences.

	Between-Person Variance				Within-Person Variance			
	Sample 1		Sample 2		Sample 1		Sample 2	
	Estimate	95% CI	Estimate	95% CI	Estimate	95% CI	Estimate	95% CI
Random Effects								
Suppression	26.7	19 , 33	35.1	30 , 40	73.3	67 , 81	64.9	60 , 70
Reappraisal	43.6	35 , 50	--	--	56.4	50 , 65	--	--
Extraversion	21.2	15 , 27	21.7	18 , 25	78.8	73 , 85	78.3	75 , 83
Social Power	50.7	41 , 57	49.1	43 , 54	49.3	43 , 59	50.9	47 , 57

Note. 95% Confidence Interval estimated using bootstrapping (999 simulations; normal approximation). Reappraisal was not measured in Sample 2.

The top panel of Figure 11 illustrates this within-person variation as density distributions for the 24 participants in Sample 1 who completed the greatest number of experience sampling surveys. Each histogram represents the distribution of one person's use of suppression across situations, centered by her or his average suppression rating. Thus, even after removing between-person differences in the stable use of suppression, there is substantial variance in people's use of suppression relative to their own mean, illustrating that people differ in their suppression use across situations.

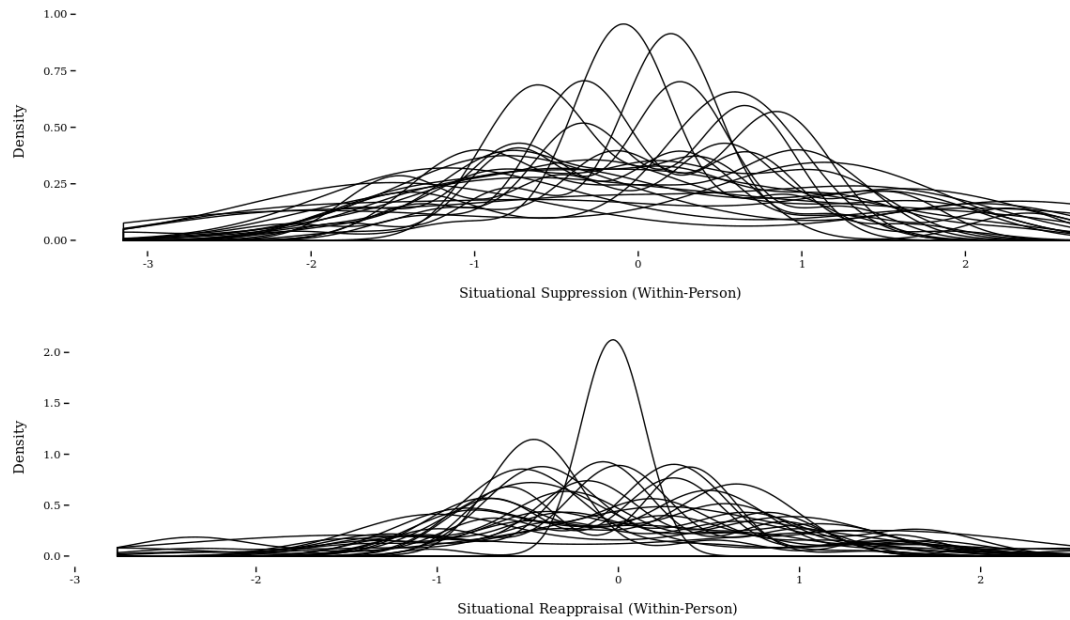


Figure 11. Density distribution of centered ratings of situational suppression use (top) and reappraisal (bottom) for participants in Sample 1 who completed at least 83% of surveys (N = 24).

In contrast, in Sample 1 I found less within-person and more between-person variation in reappraisal. The 95% confidence intervals for reappraisal do not overlap with the 95% confidence intervals for suppression, suggesting that participants varied less in their use of reappraisal across multiple situations than they varied in suppression. This effect is illustrated by the bottom panel of Figure 11, where after accounting for individual differences there appears to be less variation in the situational use of reappraisal.

Within-person variation in extraversion. I also examined within-person variation in extraversion and social power as a baseline for within-person variation in emotion regulation. Individual differences explained a significant percentage of variance in extraversion (Sample 1 $\sigma^2 = 21.2\%$, *95% CI* [15, 27]; Sample 2 $\sigma^2 = 21.7$; *95% CI* [18, 25]). This pattern closely matches the 22% of variance explained by between-person differences reported by Fleeson and Gallagher (2009) in their meta-analysis of fifteen of their own experience sampling studies. This convergent finding not only serves as an external replication of Fleeson & Gallagher's (2009) findings, but also suggests that my methodological and statistical approach is representative of other experience sampling research.

Question 2: When Do People Use Suppression?

The substantial within-person variance estimates for suppression raises the possibility that there are additional situation-specific and personality factors beyond stable individual differences that account for when people use suppression. Below, I consider the objective features of the situation before examining how suppression use varies as a function of both stable and situational differences in personality.

Hypothesis 2A: Situational suppression use varies according to objective features of the situation. To test the prediction that suppression use varies according to objective features of the situation, I built a linear multilevel model to predict suppression use from a categorical variable of the types of situations participants were in, a categorical variable of the number of people participants interacted with in each situation, and a random intercept for participant (which controls for between-person effects). Below I report the amount of variance in suppression explained by each factor relative to the random intercept model used to test Hypothesis 1.

Together, what people were doing and how many people they were with

explained around 16 percent of the variance in situational suppression use in Sample 1, and 11 percent of the variance in Sample 2. Chi-Square tests of fit suggest that both what participants were doing (Sample 1 $\chi^2 = 142$, $df = 26$, $p < .01$; Sample 2 $\chi^2 = 123$, $df = 26$, $p < .01$) and the number of people participants were with (Sample 1 $\chi^2 = 109$, $df = 6$, $p < .01$; Sample 2 $\chi^2 = 278$, $df = 6$, $p < .01$) independently contributed to a significant improvement in model fit. Both objective features of the situation appeared to explain a significant percentage of variance in the situational use of suppression. Estimates of the variance inflation factor for regression terms reported in this chapter were all less than three, which is well beyond the recommended cutoff of 10 (Kutner, Nachtsheim, & Neter, 2004), and suggest that multicollinearity was not a problem.

Figure 12 illustrates these effects by graphing situational suppression use as a function of what people were doing (top half) and how many other people participants were interacting with (bottom half). Suppression scores are reported in relation to the average; positive scores indicate that participants reported using suppression more in that situation than they did on average, whereas negative scores indicate that participants reported using suppression less in that situation than they did on average. Across both Sample 1 (left side) and Sample 2 (right side), participants were more likely to report using suppression when they were studying and reading, and less likely to use suppression when they were talking, playing, and arguing.

The number of people participants interacted with also appeared to explain variance in the situational use of suppression. Surprisingly, participants reported using suppression more when they were alone than with others in both samples. This suggests that suppression is not exclusively an interpersonal emotion regulation strategy, but might be used even in situations where people are alone.

The error bars for these effects, however, illustrate that the objective features of the situation do not necessarily determine whether people use suppression or not. Indeed, even when including both what participants were doing and who they were with in a model to predict situational suppression use, the majority of variance in situational suppression use remains unexplained (Sample 1 residual variance = 59%; Sample 2 residual variance = 54%).

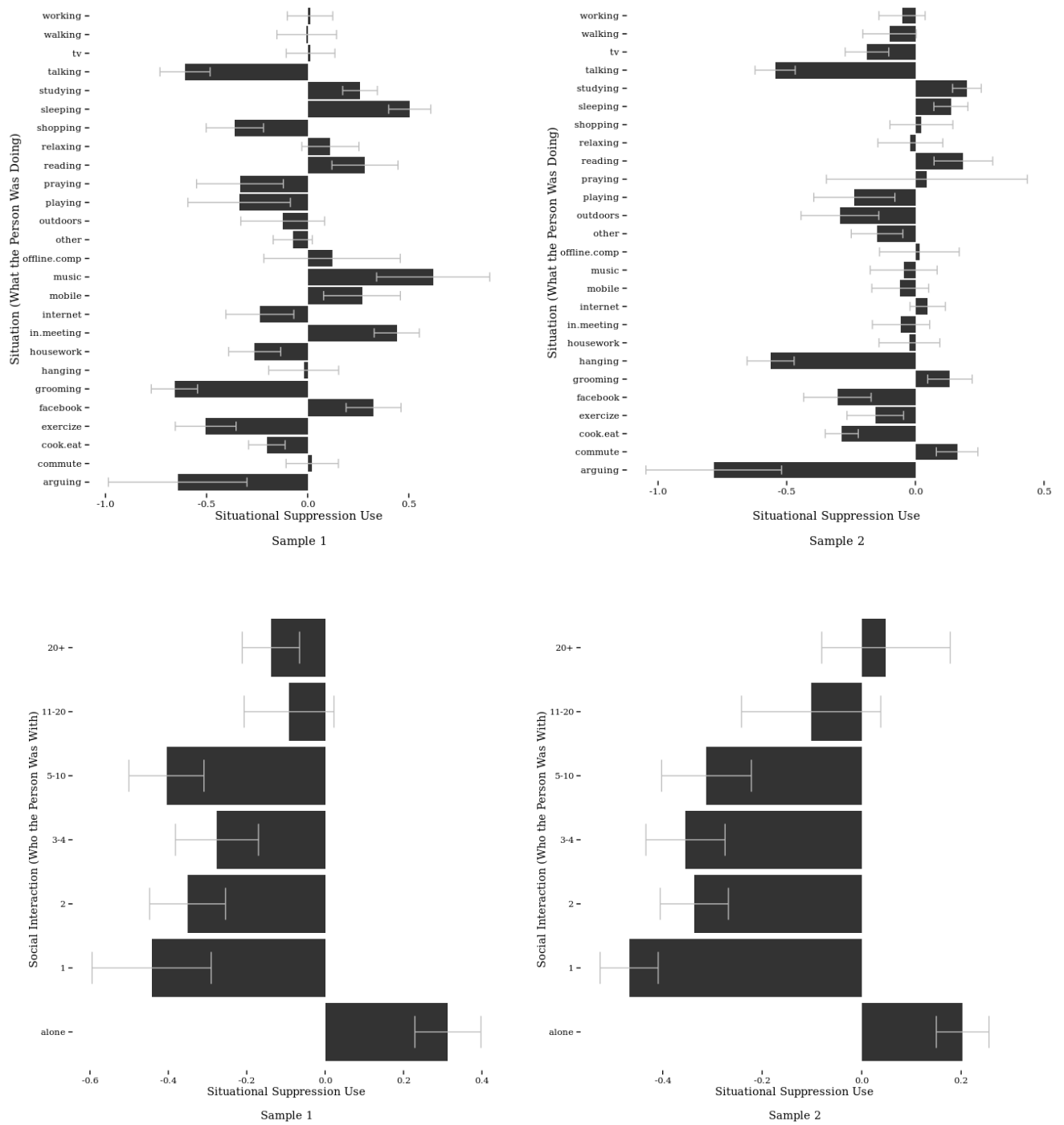


Figure 12. Variance in situational suppression explained by what the person was doing (top half) and how many people she or he was with (bottom half) in Sample 1 (left panel) and Sample 2 (right panel). Note: Effects relative to the average situational use of suppression.

Hypothesis 2B: Situational Suppression Use Varies According to Features of the Person. To determine whether situational suppression use might vary as a function of stable and situational differences in a person's level of extraversion and social power, I tested several additional linear multilevel models. Specifically, I predicted suppression use from between-person measures of extraversion and social power (i.e., how participants rated their extraversion and social power on average) and within-person measures of extraversion and social power (i.e., how participants rated their extraversion and social power in specific situations, relative to their own average.) As before, I included a random intercept to account for individual differences in the use of suppression.

Table 4.

Multilevel Models: Predicting Suppression Use from Stable and Situational Individual Difference Measures.

		Standardized Regression Estimates							
		Null Model		Full Model		Social Power		Extraversion	
Random Effects									
		<i>S1</i>	<i>S2</i>	<i>S1</i>	<i>S2</i>	<i>S1</i>	<i>S2</i>	<i>S1</i>	<i>S2</i>
Individual Differences		.27	.34	.13	.31	.13	.34	.22	.32
	Residual	.73	.63	.62	.53	.62	.60	.73	.53
Fixed Effects									
	Intercept	.00	-.01	-.01	-.01	-.01	-.01	-.01	-.01
Stable									
	Extraversion	--	--	-.02	-.29 *	--	--	-.21 *	-.16 *
	Social Power	--	--	-.36 *	.17 *	-.38 *	-.01	--	--
Situational									
	Extraversion	--	--	-.01	-.27 *	--	--	-.07 *	-.30 *
	Social Power	--	--	-.33 *	-.05 *	-.33 *	-.18 *	--	--
	Day	.02	.00	.02	-.01	.02	.01	.02	-.01
	Hour	-.07 *	-.06 *	-.04 *	-.02	-.04 *	-.05 *	-.07 *	-.02
Model Fit									
	<i>Deviance</i>			3729.5	8495	3730	8928	4018	8537
	<i>Comparison to Null</i>			$\chi^2=315*$	$\chi^2=650*$				

Note. * = 95% Confidence Interval (estimated using bootstrapping; 999 simulations; normal approximation) does not include 0. S1 = Sample 1; S2 = Sample 2. All variables standardized (Z-scored) before being entered into the regression equation.

Table 4 reports the results from a model predicting suppression use from the random intercept alone, the full model described above, as well as models predicting suppression use from stable and situational effects of social power and extraversion separately.

Across these models, situational social power emerged as the only reliable and significant predictor of suppression use. Participants who rated themselves as having less power in a specific situation were significantly more likely to use suppression in that situation (Sample 1 $\beta = -.33$, 95% CI [-.37, -.29]; Sample 2 $\beta = -.05$; 95% CI [-.07, -.02]) than were participants who rated themselves as having more power in the situation.

I replicated past research and found that stable individual differences in extraversion were negatively related to suppression use (Sample 1 $\beta = -.21$, 95% CI [-.33, -.09]; Sample 2 $\beta = -.15$; 95% CI [-.27, -.06]), suggesting that people who tend to be extraverted on average tend to use less suppression on average. The situational use of extraversion also appeared to be related to situational suppression use (Sample 1 $\beta = -.07$, 95% CI [-.11, -.03]; Sample 2 $\beta = -.30$; 95% CI [-.32, -.28]). Replicating work by Anderson, John, and Keltner (2012), social power and extraversion were related at the between-person level (Sample 1 $r = .53$; Sample 2 $r = .66$) and within-person level (Sample 1 $r = .18$; Sample 2 $r = .47$), and when accounting for stable and situational differences in both extraversion and social power, only social power explained a significant amount of variance in suppression use in both Sample 1 ($\chi^2 = 259$, $df = 1$, $p < .01$) and Sample 2 ($\chi^2 = 13$, $df = 1$, $p < .01$).

Finally, I tested whether suppression use would be best predicted by concurrent changes in social power, or changes in social power from the previous assessment. The results of these lagged analyses were non-supportive of a causal relationship. Situational suppression was best explained by concurrent ratings of social power, and this effect remained significant even when controlling for the person's situational suppression and social power in the previous assessment. This suggests that situational suppression use is explained by the person's social power in that moment, and is not a product of the person's use of suppression or capital in the previous situation.

Question 3: Why Do People Use Suppression?

Together, these findings support my prediction that broad individual

differences and situation-specific differences in personality would explain when people used suppression in real-life. That social power was the strongest predictor of stable and situational suppression use across situations suggests that people use suppression in situations where they feel low in power, status, and class, and raises the possibility that maladaptive consequences of suppression might be driven, in part, by features of the situation.

Hypothesis 3: Situational Suppression Use is Adaptive in Situations Where Participants Report Being Low Power. To test this possibility, I examined whether suppression use might hold adaptive functions in situations where people report being low in social power. Specifically, I used a multilevel model to predict well-being from stable and situational suppression use, social power, and their interaction. As before, I included a random intercept to account for individual differences. I also included a random slope coefficient for suppression, which describes the amount which the relationship between suppression use and well-being varies for different people. A substantial percentage of variance in this random slope coefficient would mean that the relationship between suppression use and well-being varies for certain individuals. (Inclusion of this random slope term does not influence the results reported below.)

Results from these models are reported in Table 5. Model 1 describes the relationship between well-being and stable and situational suppression use. Replicating past research (Nezlek & Kuppens, 2008; Impett et al., 2012; English & John, 2013), individuals who generally use suppression generally have lower well-being (Sample 1 $\beta = -.28$, 95% CI [-.39, -.17]; Sample 2 $\beta = -.17$; 95% CI [-.27, -.06]). However, I also found that situational suppression use was negatively related to well-being (Sample 1 $\beta = -.21$, 95% CI [-.27, -.15]; Sample 2 $\beta = -.20$; 95% CI [-.15, -.24]), suggesting that in situations where people report using suppression more than they normally do, they report less well-being than they do on average. These effects are illustrated in the top panel of Figure 13, which displays the relationship between well-being and stable suppression (left panel) and situational suppression (right panel) in Sample 1.

There was also small, but non-zero amount of variance in the relationship between suppression use and well-being within-participants (Sample 1 $\sigma = 1\%$, 95% CI [.1%, 2%]; Sample 2 $\sigma = 3\%$, 95% CI [2%, 4%]). Thus, the negative relationship between suppression and well-being is not

Table 5.

Multilevel Models: Predicting Well-Being from Stable and Situations Suppression Use and Social Power.

	DV: Well-Being					
	Model 1 (Suppression)		Model 2 (Suppression + Power)		Model 3 (Suppression * Power)	
	<i>S1</i>	<i>S2</i>	<i>S1</i>	<i>S2</i>	<i>S1</i>	<i>S2</i>
Random Effects (Variances)						
Participant	.33	.63	.21	.38	.22	.36
Suppression Slope	.01	.03	.01	.02	.01	.02
Residual	.72	.58	.65	.46	.64	.46
Fixed Effects (Standardized Betas)						
Intercept	.02	-.01	.02	-.02	-.06	-.03
Day	-.08 *	-.06 *	-.09 *	-.07 *	-.08 *	-.07 *
Hour	.04 *	.02 *	.02	.00	.02	.00
<i>Suppression Use</i>						
Stable (.X)	-.28 *	-.17 *	-.08	-.14 *	-.07	-.15 *
Situational (.S)	-.21 *	-.20 *	-.10 *	-.12 *	-.11 *	-.12 *
<i>Social Power</i>						
Stable (.X)	--	--	.31 *	.31 *	.30 *	.31 *
Situational (.S)	--	--	.28 *	.36 *	.27 *	.36 *
<i>Interaction</i>						
Suppression.S * Power.S	--	--	--	--	-.08 *	-.03 *
Suppression.S * Power.X	--	--	--	--	-.01	-.01
Suppression.X * Power.S	--	--	--	--	.01	.02
Suppression.X * Power.X	--	--	--	--	-.07 *	.01
Model Fit						
<i>Deviance</i>	3955	8818	3758	7953	3733	7940

Note. * = bootstrapped 95% CI does not include 0. S1 = Sample 1; S2 = Sample 2

fixed for every person, but varies somewhat depending on the person. As seen in Model 2, variation in well-being was also explained both by stable and situational differences in social power. People who tend to be high in social power have greater overall well-being (Sample 1 $\beta = .31$, 95% CI

[.19, .45]; Sample 2 $\beta = .31$; 95% CI [.23, .40]), and people report having more well-being than they do on average in situations where they have more social power than they do on average (Sample 1 $\beta = .28$, 95% CI [.24, .32]; Sample 2 $\beta = .36$; 95% CI [.33, .38]). Critically, including these parameters in the model diminished the relationship between well-being and both stable suppression use (Sample 1 $\beta = -.08$, 95% CI [-.21, +.06]; Sample 2 $\beta = -.14$; 95% CI [-.24, -.06]) and situational suppression use (Sample 1 $\beta = -.10$, 95% CI [-.16, -.05]; Sample 2 $\beta = -.12$; 95% CI [-.16, -.09]). This substantial reduction in variance in well-being explained by suppression when accounting for the effects of social power on well-being is illustrated in the middle panels of Figure 13. One reason suppression holds negative consequences is that people who tend to suppress tend to be low in social power, and people tend to use suppression in situations where they tend to be low in social power.

In Model 3, I tested whether the negative relationship between suppression use and well-being would be moderated as a function of people's stable or situational social power. As predicted, I found a small but statistically significant interaction effect between situational suppression and situational social power in both samples (Sample 1 $\beta = -.08$, 95% CI [-.11, -.05]; Sample 2 $\beta = -.03$; 95% CI [-.05, -.01]).

The bottom right-hand panel of Figure 13 illustrates this interaction effect as simple slope estimates that describe the relationship between situational suppression use and well-being for participants in Sample 1 who scored one standard deviation above the mean in social power (solid line) and participants who scored one standard deviation below the mean in their situational social power (dashed line). When participants are in situations where they are lower in social power they they are on average, the relationship between suppression use and well-being (Sample 1 $\beta = -.03$; Sample 2 $\beta = -.09$) than when participants are in situations where they are higher in social power than they were on average (Sample 1 $\beta = -.19$; Sample 2 $\beta = -.15$). (The bottom left-hand panel illustrates the between-person interaction effect in Sample 1, although it bears repeating that this interaction effect did not replicate in Sample 2.)

I also found marginal evidence that stable individual differences in social power moderated the relationship between stable suppression use and well-being in Sample 1 ($\beta = -.07$, 95% CI [-.14, .01]). This effect is illustrated on the bottom left-hand panel of Figure 13, and demonstrates

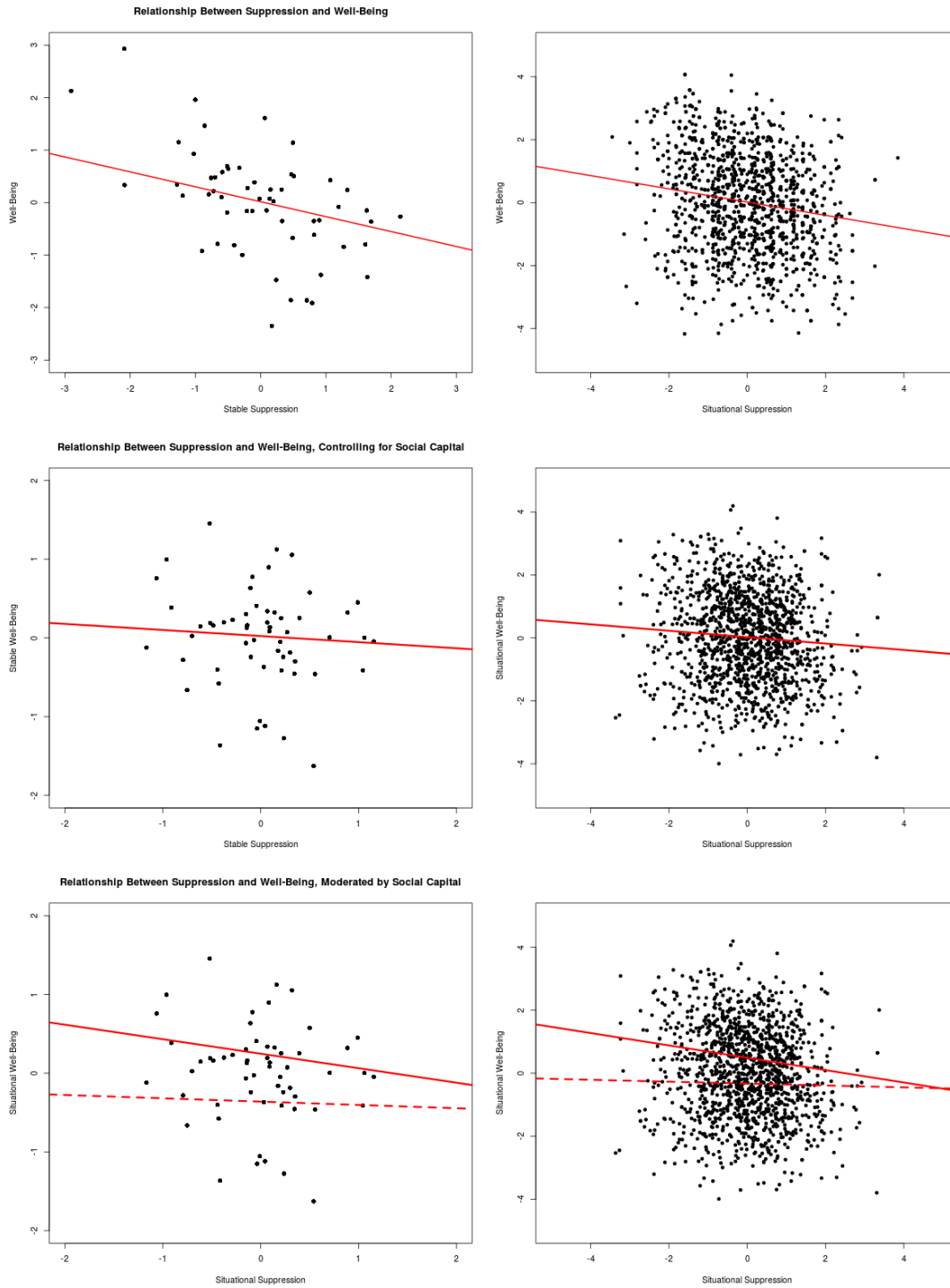


Figure 13. Predicting well-being from stable (left side) and situational (right side) use of suppression (top panel); suppression controlling for effects of social power (middle panel); suppression moderated by social power (bottom panel) for participants one standard deviation above the mean in social power (solid line) and one standard deviation below the mean in social power (dashed line).

that the relationship between people's stable use of suppression and stable self-esteem is negative only for people who tend to be high in social power. However, the 95% Confidence Interval for this effect included zero, and this pattern of effects did not replicate in Sample 2 (Sample 1 $\beta = .01$, 95% CI [-.08, .08]).

Additional analyses demonstrate that these interaction effects remain significant when included in the model alone, that the relationship between suppression and well-being does not seem to be significantly moderated by extraversion nor does well-being appear to moderate the relationship between situational power and suppression use. Only situational social power significantly moderated the relationship between situational suppression use and well-being in both samples.

Finally, I conducted lagged analyses to test whether the use of suppression in situations where participants feel low in social power would predict changes in *future* well-being. These lagged interaction effects were not significant: situational suppression use does not lead to subsequent changes in well-being.

General Discussion

Across two samples, I found evidence for considerable variation in how people use suppression in everyday life situations. Whereas past research has identified ways in which suppression can be used in response to specific situations (Srivastava et al., 2009; McRae et al., 2011) or on a day-to-day basis (e.g., Nezlek & Kuppens, 2008; Le & Impett, 2013), these findings are the first to demonstrate the extent to which suppression use varies across real-life situations. This variation in suppression use does not appear to be random error, but instead is explained both by objective features of the situation as well as the person's subjective appraisal and personality across situations. These results suggest that although stable individual differences in suppression use exist and predict important social and well-being outcomes, they appear to only describe a moderate percentage of variation in how people use suppression.

My goal in conducting these analyses was not to provide a comprehensive and definitive account of the features of situations in which people suppress. Rather, my findings provide empirical evidence that describes suppression more as a dynamic processes than as a static process that people use indiscriminately across situations or social interactions. Below, I discuss the implications of these findings, and describe future

research directions that might address limitations of the current approach and help advance the science of emotion regulation research.

Is Suppression Bad, or Does it Happen in Bad Situations?

In this chapter, I present converging evidence across two samples that suppression use is not always maladaptive. Rather, I found that suppression use is likely to occur in situations where people feel low in social power, and that when the effects of social power are taken into consideration, suppression use appears to be less maladaptive. That the relationship between suppression use and well-being was explained, in part, by the relationship between suppression and social power provides empirical evidence in support of social functionalist accounts of emotion (e.g., Keltner & Haidt, 1999).

These findings, however, are not inconsistent with the considerable body of past research on emotion regulation that demonstrates the negative intra- and interpersonal consequences associated with stable individual differences or experimentally manipulated suppression use (e.g., Gross & Levenson, 1993; Gross & John, 2003; John & Gross, 2004; Butler et al., 2003; Nezlek & Kuppens, 2008; English & John, 2013). Indeed, I replicated past work by showing that the stable use of suppression is related to reduced well-being. However, these findings suggest that suppression use might be an important regulation strategy that helps certain people in certain situations avoid punishments. Future research on emotion regulation might examine whether people strategically use suppression in certain situations or relationship contexts in order to achieve certain outcomes. For example, although past research suggests that people who tend to use suppression tend to have less close relationships with others, it is possible that people use suppression in part because they feel less close to those others.

Testing for causality of suppression's effects. One limitation of the current study is that I was not able to establish causality for the relationship between suppression and social power, or for the moderating effect of social power on the relationship between suppression and well-being. Multilevel regression analyses using lagged effects for predictors and dependent variables yielded consistent results - the effects of social power on suppression (and on suppression's relationship to well-being) appear to be best described by concurrent effects. The null results of these lagged analyses hold three different possibilities.

First, it is possible that relationships between suppression and

social power are simply correlational artifacts of general response tendencies. Supplementary analyses refute this idea by demonstrating that 1) the relationship between suppression and social power remains significant even when accounting for extraversion, 2) that the relationship between suppression and well-being is not moderated by extraversion, but only by social power, and 3) that well-being did not moderate the relationship between situational capital and suppression use. Together, these results suggest that the correlational relationships are specific to social power and suppression.

Second, it is possible that the experience sampling methods used in this study were not properly calibrated to identify lagged effects of suppression on well-being. Participants were assessed at two hour intervals; the consequences of using suppression on future well-being might be more immediate (which would require more frequent assessments) or less immediate (which would require less frequent assessments). Indeed, I did not find any lagged effects of suppression alone on well-being. Future research might employ other kinds of repeated measures designs, such as the day reconstruction method (Kahneman et al., 2004), or a more intensive experience sampling approach in order to account for more nuanced causal processes.

Third, it is possible that the effects of social power on suppression are concurrent; that is, suppression is used in situations where people feel low in social power. It's unclear, then, whether changes in social power at one time point would lead people to use suppression at another time point.

Although lagged effects are often used to make claims about causal processes (e.g., Bolger & Laurenceau, 2013), experimental manipulation is considered the gold standard for determining causal relationships. Thus, even in the presence of null lagged effects, it remains unclear whether social power causes people to use suppression, or whether suppression use causes people to feel low in social power. Future research might employ social psychological techniques to determine whether experimentally manipulating a participant's social power. Like most things in life, it's likely that there exists a bi-directional relationship, in which expressive suppression is not only used by people low in social power, but also functions to keep people there.

Can suppression be "good"? I did not find evidence that suppression had *positive* outcomes; at best suppression use appears to be

non-negatively related to well-being. This suggests that suppression might act more as a buffer against negative outcomes than as a beneficial emotion regulation strategy like reappraisal. Although reappraisal still remains the gold-standard for an effective and beneficial emotion regulation strategy, it's not clear that every situation can be reappraised in an adaptive way. Suppression might therefore serve as a "handbrake" that helps prevent people from suffering negative consequences as a result of expressing certain emotions in certain situations.

Future research might examine other individual difference and situations-specific features to determine when, where, and for whom suppression use can be adaptive. Another limitation of this study is that I did not measure people's goals for using suppression in specific situations, though emerging research suggests that suppression use can have different outcomes depending on the person's culture or relationship specific goals (Impett et al., 2012; English & John, 2013; Le & Impett, 2013). Future research might seek to help people learn to identify the kinds of situations and social interactions in which it is adaptive and maladaptive to use suppression. Such research might allow clinicians to help people more effectively regulate their emotions by identifying the kinds of situations in which it is more or less beneficial to use suppression.

Understanding Who and When People Use Emotion Regulation in Real-Life Contexts

Whereas past approaches define emotion regulation in terms of the component of emotion that each strategy affects (Gross, 1998b), this chapter also demonstrates that emotion regulation strategies can differ in the way that they are used across different situations. For example, reappraisal appears to be used more consistently across situations than suppression, although I was not able to test whether this effect would replicate in Sample 2.

Across both samples, I also found replicating patterns in the kinds of situations in that people reported using suppression. For example, although past research has emphasize the interpersonal nature of expressive suppression (Gross, Richards, & John, 2006; Campos et al., 2011), these results suggest that people also use suppression in non-social situations. Future research might examine differential consequences associated with using suppression in social vs. non-social situations. Researchers seeking to better understand how emotion regulatory processes

differ might borrow methods from emotion appraisal literature to identify whether there are certain situations in which strategies like suppression and reappraisal are more or less likely to be used.

Although understanding within-person variation in suppression was the focus of this study, the situation-specific framework used in this chapter might also be applied to address new and existing questions about reappraisal and other emotion regulation strategies. For example, while reappraisal exhibited substantially more stability across situations than suppression, I found evidence that people varied in their use of reappraisal across situations. What situations do people use reappraisal in? Are people always able to use reappraisal when they want to, or are there some situations in which they want to reappraise but cannot find a way to reframe the situation? In the same way that a maladaptive emotion regulation strategy like suppression can serve adaptive social functions, are there ways and situations in which reappraisal might hold negative intra- or interpersonal consequences?

Furthermore, the experience sampling method used in this chapter might be adapted to study other emotion regulatory processes. Though suppression and reappraisal dominate the emotion regulation literature (Gross & Thompson, 2007), other emotion regulation strategies operate by changing the way people interact with their situations. Future research might examine how people approach or avoid situations in order to change their emotions (Gross, 2009). These findings suggest that researchers seeking to understand why people use a maladaptive emotion regulation strategy might examine how people use suppression in specific situations.

CHAPTER 4: CONCLUSION

The goal of this dissertation has been to demonstrate how a within-person approach to personality enables researchers to ask and answer new questions about psychological processes. In Chapter 1, I introduced this dissertation with a description of the conceptual reasons for studying within-person variation, a summary of the assessment and analytic methods that underlie the within-person approach to research, and an outline of three broad research questions that can be tested through within-person methods. In Chapters 2 and 3, I demonstrated the relevance of within-person variation to different psychological phenomenon by testing hypotheses related to how a person varies in her or his level of social hierarchy or use of suppression across different situations. In this final chapter, I summarize the major findings from Chapters 2 and 3 as they relate to the three broad research questions outlined in Chapter 1, and discuss the broader contributions and limitations of this dissertation research. I then conclude with a discussion future research directions.

Three Within-Person Research Questions

How Much Within-Person Variation is There?

In Chapter 2, I found that three related hierarchical dimensions - social power, status, and class - exhibited different patterns of within-person variation. Social power was the least stable dimension of social hierarchy, and exhibited the most within-person variation compared to social status and social class. In contrast, social class was the most stable dimension of social hierarchy, and exhibited significantly less within-person variation compared to social power. Social status, in turn, fell in between social power and class in its degree of within-person variation.

In Chapter 3, I found substantial within-person variation in people's use of expressive suppression - a response-focused strategy that regulates the way a person displays his or her emotion in the face and body. In contrast, I found less within-person variation in people's use of cognitive reappraisal - an antecedent-focused strategy that regulates emotion by changing a person's construal of a situation. Someone who uses reappraisal in one situation is more likely to use it in other situations than someone who uses suppression in one situation. This finding suggests that cognitive reappraisal represents more of a stable individual difference in ability than expressive suppression, which appears to vary from situation to situation.

That ratings of social class still exhibited substantial within-person variation (albeit significantly less variation than social power) suggests that even broad psychological dimensions that are influenced by relatively stable background characteristics are dynamic at the level of a person's self-perceptions. In fact, every variable reported in this dissertation, along with variables from other research on emotion and personality, demonstrate substantial within-person variation in other psychological dimensions.

Such research raises the possibility that *all* psychological processes operate within-persons. This idea is falsifiable using conventional research methods, and researchers may one day uncover some psychological process that is entirely stable across situations. However it's difficult to imagine a domain of human thought, feeling, or behavior that is invariant across all social contexts. Human life is complex, our situations and relationships change from moment to moment, and self-perceptions are likely to be dynamic to the extent that they are shaped by these varying environmental factors.

Rather than seek to determine *if* a specific psychological domain varies within persons, researchers might instead focus on *how* that domain varies within-persons compared to other related psychological domains. In this dissertation, I took this approach by contrasting the amount of within-person variation in suppression use to reappraisal, and comparing the amount of within-person variation among related dimensions of social hierarchy. Researchers interested in examining within-person processes in their own fields of research will need to identify relevant dimensions for comparison that are based on existing theory and research.

What Predicts Within-Person Variation?

A second goal of this dissertation was to describe the sources of within-person variation in expressive suppression and social hierarchy. Specifically, I examined whether within-person variation would be explained by features of the situation (i.e., what the person was doing and who the person was with) as well as features of the person (i.e., what the person was like in a specific situation.)

In Chapter 2, I found that hierarchical dimensions like social power, status, and class differ in their sources of within-person variation. Furthermore, this differentiation followed patterns consistent with past theory on social hierarchy. For example, whereas the situation a person was in was a strong source of within-person variation in social power (which is based on a person's construal of his or her ability to

influence a situation), the number of other people in the situation was a stronger source of within-person variation in social status (which is based on others' evaluations of the self) than either social power or class.

In Chapter 3, I found that suppression use varied as a function of both what the person was doing and with whom the person was. However, one of the strongest sources of variation in expressive suppression was the person's level of social power in a specific situation. More specifically, I found that people are more likely to report using suppression in situations where they feel low in social power and status than in situations where they feel high in these hierarchical dimensions.

In both chapters, I identified specific features of the situation and relationship context that influenced whether a person felt more or less of a psychological dimension than she or he did on average. Although these effects replicated across both samples, it's unclear to what extent these effects of *specific* social and relationship context self-perceived social hierarchy or suppression use will generalize to populations outside of the Berkeley undergraduate students sampled in this dissertation. For example, I found that ratings of social class were significantly higher than average when participants were talking with another person. These conversations were likely between Berkeley students aware of their relative privilege in society; social class during conversations might very well be significantly lower than average when measured for other groups of people.

I place somewhat more confidence in effect of the broader relationship between what the person was doing and social class. In contrast to the effect of "having a conversation" (a specific level of the broader factor) on social class, the effect of "what the person was doing" (the broader factor) on social class is more likely to generalize to other populations because it aggregates the noise associated with specific situations. That is, low-level employees at a large corporation may not feel high in class when on the phone (inconsistent with my research), but will be more likely to vary little in class as a function of what they are doing (consistent with my research).

For the same reason, I would expect that relationships between people's self-perceptions will generalize between populations, since these self-perceptions are likely to be less dependent on the specific population. An undergraduate student may feel lower in power when working than a corporate executive would feel, however the experience of low power

is likely to be similar for each.

Regardless of my confidence (which both social psychological research and real-life experience informs me can often be a poor metric to place faith in), these expectations can be tested empirically. To determine how these effects generalize in other populations, I might use experience sampling methods (or other methods of within-person assessment) with non-student populations, and evaluate not only whether my effects replicate, but also whether the effects of specific situations are more or less likely to replicate than the effects of more general features of situations or persons.

What Does Within-Person Variation Predict?

The third goal of this dissertation was to examine the ways in which within-person variation might itself predict behavior. The repeated measurement required for studies of within-person variation allows researchers to conduct cross-lagged analyses, in which they test whether changes in one construct predict later changes in another.

In Chapter 2, I found that changes in social class predicted subsequent changes in social power and status, but changes in social power and status did not predict subsequent changes in social class. When someone feels like she or he climbs the social ladder, the benefit she or he receives "trickles down" to his or her feeling of power and status in later interactions.

In Chapter 3, I found that the situational use of suppression was less negatively related to well-being than the stable use of suppression. Furthermore, I found evidence that when people use suppression in situations where they feel low power, they suffer no negative consequences for well-being. However, cross-lagged analyses were not significant: the interaction effect only held for variables measured at the same time. This raises two alternative explanations: either this pattern of associations is not causal, or the experience sampling method used in this study did not have the needed power or precision to detect a causal relationship.

Together, these findings demonstrate the ways in which within-person methods of assessment can challenge existing ideas and advance understanding about psychological processes. Though cross-lagged analyses are often used to make claims about causal processes, experimental manipulation remains the "gold standard" for establishing causality in scientific research. These correlational findings should therefore be supplemented with experimental research.

Future Research Directions

Mapping Uncharted Domains of Within-Person Variation

Like past research, this dissertation focuses on psychological variables that historically have been studied through between-person methods. However, future research should examine the potential for within-person methods of assessment to examine variables that are difficult to be studied through broad individual difference measures or experimental manipulations.

For example, one emotion regulation strategy that has received little attention in psychological research is *situation selection* - a strategy in which people regulate their emotions by changing the situation they are in. (The example that I use with my students is that since I don't like being startled, I don't go to scary movies.) Using experience sampling methods, researchers might be able to ask participants about the extent to which they used situation selection to seek out their current situation (or avoid their previous situation.)

Other research might examine the utility of using experience sampling methods to administer interventions. Researchers might use a series of "if-then" commands to trigger a relevant message in the context of certain situations, emotions, or self-appraisals. For example, researchers interested in helping people avoid digital distractions might remind people to turn off their computer if the person is online and experiencing low self-esteem.

Best Practices

Research insights are only as valid and reliable as their methods, and within-person methods of assessment require researchers to make many decisions about how to collect data. For example, in terms of administering surveys to participants, researchers need to decide when to schedule assessments, how many assessments to schedule, and whether the schedule should be consistent, random, or determined based on some feature of the situation (e.g., when the person is detected to be with others).

Each decision has the potential to influence the researchers' results. For example, asking participants to rate their use of suppression each day over the course of a month (for a total of 30 assessments) may not provide the level of precision required to study the kinds of situations in which suppression use holds adaptive consequences.

What are the best-practices of experience sampling research? Though some researchers have outlined the decisions that are possible or offered suggestions based on their own experiences, no research has yet conducted a methodological meta-analysis to evaluate the decisions researchers make

about how many surveys to administer, that are likely to influence effect estimates and the power to detect them.

On Learning More About Persons.

Potential insights gained from an attempt to document "best-practices" in experience sampling methods may be short-lived. By the time this dissertation is published and read, new methods of within-person assessment will likely have been developed. Advances in technology have reduced the cost of acquiring participant data, and academic and industry researchers of the future will be able to learn about what people are like with increasing levels of precision. Existing devices and techniques can already measure a person's exact location (GPS), real-time emotion (vocal data), and physiological behavior (heart rate monitors on watches). Researchers can expect that other variables will soon be available for analysis, and as real-life moves into the digital environment, every click, movement, and behavior will be logged for future analysis.

Only time will tell what consequences this trend toward total quantification of the self will hold for society. For psychologists, these methods will provide a level of precision and access to populations that were previously inconceivable. Indeed, "big data" approaches to psychology are beginning to analyze large sets of data to answer new questions about between-person effects; researchers and data scientists will likely soon begin to examine precise patterns of consistency and change in people's behavior using within-person methods. With enough participants and precise measures of human behavior, psychological science may be able to develop models that predict human behavior with startling accuracy in real-time.

Yet it is unclear whether this endeavor is possible, or even good for the field. Allport (1955) felt that the failure among psychologists to take an interest in "the existential richness of human life" wasn't *just* a matter of methodological limitations. In the quotation I introduced this dissertation with, Allport continues to write:

Methods, they say, are lacking. Or, more exactly stated, the methods available fall short of the stringent requirements laid down by modern positivism. In their desire to emulate the established sciences psychologists are tempted to tackle only those problems, and to work on only those organisms, that yield to acceptable mathematical psychology highly developed. So dominant is the positivistic ideal that other fields of psychology came to be regarded as not quite reputable. Special aversion attaches to problems having to do with complex motives, high-level integration,

with conscience, freedom, self hood. As we have said, in large part it is the relative lack of objective methods of study that accounts for this aversion. But the explanation lies also in the preference of positivism for externals rather than internals, for elements rather than patterns, for geneticist, and for a passive or reactive organism rather than for one that is spontaneous and active. (p. 11-12)

In the modern era of "big data", social and personality psychologists are closer to emulating the hard sciences today than they were fifty years ago. To what extent should researchers' questions be guided by information made available to them by companies that promote modern technologies? What aspects of human life are ignored by such methods? Might effects in psychology fail to replicate in part because human life does not reduce to statistical models? To ensure psychology captures the full extent of human life, future research should balance this march toward positivistic progress with qualitative approaches.

In this dissertation, I sought to capitalize on recent methodological advances to advance psychologists understanding of social hierarchy and emotion regulation processes. However, it is unclear whether these insights were dependent on these new methods. Do researchers need to be convinced by quantitative data that there are contexts in which hiding emotions from others can be adaptive? Would qualitative methods (or even anecdotes that resonate with readers) allow for similar insights?

Summary

People are not static, but exhibit remarkable change as they go from one situation, relationship context, or moment in time to another. In order to model this change, researchers need methods that allow for multiple assessments of people's thoughts, feelings, and behaviors across a variety of real-life situations and social interactions. This within-person approach has the potential to not only advance researchers' understanding of complex psychological processes, but also allow researchers to develop tools that might help people learn how to best navigate what Allport called the "existential richness of everyday life."

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APPENDICES

Complete List of Measures

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Summary of Data Cleaning, Filtering Procedures, and Descriptive Statistics

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Key to Samples:

Sample A: Used as Sample 1 in Chapter 2.

Sample B: Used as Sample 2 in Chapter 2 and Sample 2 in Chapter 3.

Sample C: Used as Sample 1 in Chapter 3.

Appendix: Complete List of Measures

Samples A and B:

sid What is your ID (Initials + birth month + day: eg. NC0401)?

sit What were you doing in the last 30 minutes (before taking this survey)?

--choose an activity-- (1)	Online social networking (11)	Talking, conversation (22)
Browsing the internet (27)	On the computer (offline) (12)	Walking, taking a walk (23)
Commuting (2)	On a mobile device. (13)	Watching television (24)
Cooking / Eating (3)	Outdoors (14)	Working (25)
Exercising (4)	Playing (15)	Other (26)
Fighting, Arguing (5)	Praying, meditation (16)	
Grooming, self-care (6)	Reading (17)	
Hanging out with friends (7)	Relaxing, doing nothing (18)	
Housework (8)	Shopping, errands (19)	
In a meeting (9)	Sleep (20)	
Listening to music, podcast (10)	Studying (21)	

emo What primary emotion were you feeling in this situation?

--choose an emotion-- (4)	embarrassed (20)
accomplished (3)	excited (21)
afraid (5)	focused (22)
amused (6)	frustrated (23)
angry (7)	grateful (24)
annoyed (8)	guilty (25)
anxious (9)	happy (26)
arrogant (10)	inspired (27)
ashamed (11)	interested (28)
bored (12)	jealous (29)
calm (13)	lonely (30)
confident (14)	loving (31)
confused (15)	sad (32)
contemptuous (16)	superior (33)
determined (17)	surprised (34)
disgusted (18)	sympathetic (35)
dismissive (19)	tired (36)

int How intense was this emotion?
 --choose an intensity-- (1)
 0 - Very Weak (2)
 1 (3)
 2 (4)
 3 (5)
 4 (6)
 5 - Moderate (7)
 6 (8)
 7 (9)
 8 (10)
 9 (11)
 10 - Very Strong (12)

val How pleasant was this emotion?
 --choose a valence (pos/neg)-- (1)
 0 - Very Negative (2)
 1 (3)
 2 (4)
 3 (5)
 4 (6)
 5 - Fair (7)
 6 (8)
 7 (9)
 8 (10)
 9 (11)
 10 - Very Positive (12)

soc How many other people were you directly interacting with in this situation?
 --choose a number of people-- (1)
 0 (I was alone) (2)
 1 (3)
 2 (4)
 3-4 (5)
 5-10 (6)
 11-20 (7)
 20+ (8)

sis In this situation...

	Not at All 1 (1)	2 (2)	Some3 (3)	4 (4)	Very Much5 (5)
I was extraverted, enthusiastic. (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I was sympathetic, warm. (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I was dependable, self-disciplined. (3)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I was open to new experiences, complex. (4)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I was reserved, quiet. (5)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I was critical, quarrelsome. (6)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I was disorganized, careless. (7)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I had high self-esteem. (8)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feared others' negative evaluations. (9)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I had a great deal of power (e.g., can exert influence). (11)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I sought out people or situations to feel a certain way. (19)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I had a lot of social status (e.g., is	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

respected by others). (12)					
I controlled my emotions by keeping them to myself. (20)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I avoided people or situations to feel a certain way. (21)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I was high in social class (e.g., has high rank in society). (13)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I controlled my emotions by changing the way I thought about the situation I was in. (16)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

oid What were the initials of the person you were interacting with?

rel How do you know this person?

- choose relationship type-- (1)
- Close friend (9)
- Friend / other student (8)
- Family member (2)
- Romantic partner (3)
- Colleague / co-worker (4)
- Boss / teacher (5)
- Employee / student (6)
- Acquaintance; stranger (7)

ois The person I was interacting with in this situation...

	Not at All (1)	2 (2)	Some 3 (3)	4 (4)	Very Much 5 (5)
Was extraverted, enthusiastic. (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Had a lot of social power (e.g., can exert influence). (6)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Had high self-esteem. (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Had a lot of social status (e.g., is respected by others). (3)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Is someone I felt close to. (4)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Keeps her/his emotions to her/himself. (5)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Was high in social class (e.g., has high rank in society). (7)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Sample C

Q9 What is your ID (Initials + birth month + birth day)?

do What were you doing just before you received this survey?

Browsing the internet (1)	Outdoors (14)
Commuting (2)	Playing (15)
Cooking / Eating (3)	Praying, meditation (16)
Exercising (4)	Reading (17)
Fighting, Arguing (5)	Relaxing, doing nothing (18)
Grooming, self-care (6)	Shopping, errands (19)
Hanging out with friends (7)	Sleep (20)
Housework (8)	Studying (21)
In a meeting (9)	Talking, conversation (22)
Listening to music, podcast (10)	Walking, taking a walk (23)
Online social networking (11)	Watching television (24)
On the computer (offline) (12)	Working (25)
On a mobile device. (13)	Other (26)

feel How did you feel in this situation?

- 0 - Very Negative (1)
- 1 (2)
- 2 (3)
- 3 (4)
- 4 (5)
- 5 - Fair (6)
- 6 (7)
- 7 (8)
- 8 (9)
- 9 (10)
- 10 - Very Positive (11)

with How many other people were you interacting with?

- 0 (1)
- 1 (2)
- 2 (3)
- 3-4 (4)
- 5-10 (5)
- 11-20 (6)
- 20+ (7)

self In this situation...

	Not at All1 (1)	2 (2)	Some3 (3)	4 (4)	Very Much5 (5)
I controlled my emotions by keeping them to myself. (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I sought out people or activities to feel a certain way. (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I was outgoing, sociable. (3)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I had high self-esteem. (4)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I was authentic. (5)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I had a lot of status. (6)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I had a lot of power. (7)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

oth (Skip these questions if you were alone.)The people I was interacting with in this situation...

	Not at All1 (1)	2 (2)	Some3 (3)	4 (4)	Very Much5 (5)
Were outgoing. (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Had high self-esteem. (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Had a lot of status. (3)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Had a lot of power. (4)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Samples A and B

Methods

Participants filled out a pre-questionnaire containing self-reports of personality and nominated peers to rate their personality; participants were then contacted via smartphone 6 times a day for 6 days, and asked to complete a variety of ratings about the situation they were in, and their emotions, behaviors, personality, and social interactions within that specific situation.

Participants

Sample Size:

- 77 participants completed the pre-questionnaire.
- 69 participants answered at least one experience sampling.
- 56 participants remain after cleaning procedures.

Sample Size = 77 pts (pre-questionnaire)

- Gender: 87% female (n = 67); 13% Male (n = 10)
- Age: Mean = 20.97; Median = 21; SD = 2.07; Range = 18 - 28
- Ethnicity: 56% Asian; 25% White; 8% Latino; 5% Middle Eastern; 5% Other; 1% Black

Sample Size = 56 pts (after cleaning); 2 pts did not provide demographic information.

- Gender: 89% female (n = 48); 11% male (n = 6)
- Age: Mean = 21.13; Median = 21; SD = 2.19; Range = 18-28
- Ethnicity: 50% Asian; 32% White; 9% Latino; 4% Middle Eastern; 4% Other; 2% Black

Procedures

Experience Sampling Filtering

- Time Spent on the Assessment:
 - Mean = 4.46; Median = 1.65; SD = 27.86; Range = .11 - 1004.68
 - Filtered by: 30 seconds - 3X SD (88 minutes); removed: 21 assessments; 0 participants
- Responses with a low standard deviation across the items
 - Mean = 1.07; Median = 1.08; SD = .42; Range = 0 - 2.1
 - Filtered: greater than .01; removed: 80 assessments; 0 pts.
- Percent of Surveys Completed:
 - Mean = 67.2%; Median = 77.8; SD = 28.43; Range = 5.6 - 108.33
 - Filtered: Completed more than 40%; removed: 92 assessments; 13 participants
- Final N = 56 participants. Two participants did not complete pre-Questionnaire.

Measures

- Educational background: 59% Cal (n = 32); 41% CC (n = 22)
- Family income:

	mom.inc	dad.inc
<15k	27.78	14.81
15-25k	7.41	7.41
25-35k	5.56	7.41
35-50k	12.96	12.96
50-75k	16.67	7.41
75-100k	7.41	14.81
100-150k	12.96	11.11
>150k	3.70	16.67
NA's	5.56	7.41
- Family level of education:

	mom.ed	dad.ed
hs	5	5
HS	8	5
c	3	4
AD	4	1
C	17	20
gs	1	0
M	11	14
PhD	5	5

Self-Report Questionnaires:

Measure	Mean	SD	Range	Alpha
Big Five Inventory (44-item)				
Extraversion	4.3	1.2	1.2 - 6.8	.89
Agreeableness	5	.86	3.3 - 6.9	.80
Conscientiousness	4.7	.76	2.6 - 6.6	.76
Neuroticism	4.1	1.2	1.8-6.6	.87
Openness	4.5	.84	2.7-6.5	.79
Sense of Power Scale (8-item)				
	4.7	.89	2.1-7	.87
Social Status Measure (5-item)				
	4.3	1.1	1-7	.95
Emotion				
Positive Affect Scale (13-items)	4.7	.75	2.5 - 6.1	.86
Negative Affect Scale (18-items)	3.4	.92	1.7 - 5.0	.90
Ambivalence over Expressivity	4.3	1.2	1 - 6.9	.89
Emotion Regulation				
Suppression (4-item)	3.5	1.2	1 - 6.3	.72
Reappraisal (6-item)	5	1	2.5 - 7	.88
Situation Selection -Approach (7-item)	5	.88	2.9 - 6.7	.73
Situation Selection-Avoidance (3-item)	4.9	1.1	2 - 7	.76
Well-Being				
Rosenberg Self-Esteem (10-item)	4.7	1.2	2 - 6.8	.93
Fear of Negative Evaluations (6-item)	4.7	1.1	2.2 - 7	.83
Interpersonal Support (12 - items)	5.3	1	3 - 6.8	.90

Authenticity (6-item)	4.6	1.1	1.7 - 6.3	.84
-----------------------	-----	-----	-----------	-----

Zero-Order Correlations Among Self-Rated Personality Constructs

	BFIE	BFIA	BFIC	BFIN	BFIO	SOP	STAT	RSE	AEQ	ERQS	ERQR	ERQAP	ERQAV	AUTH	FNE	ISEL
BFIE	1.00	-0.14	0.29	-0.26	0.28	0.60	0.58	0.40	-0.36	-0.36	0.25	0.14	0.21	0.45	-0.34	0.34
BFIA	-0.14	1.00	0.41	-0.37	0.11	0.15	0.10	0.15	0.10	-0.04	0.32	0.31	0.20	0.03	0.39	0.38
BFIC	0.29	0.41	1.00	-0.41	0.36	0.42	0.34	0.35	-0.14	-0.22	0.12	0.31	0.31	0.28	0.01	0.44
BFIN	-0.26	-0.37	-0.41	1.00	-0.11	-0.39	-0.35	-0.62	0.22	-0.07	-0.36	-0.13	-0.34	-0.40	0.21	-0.30
BFIO	0.28	0.11	0.36	-0.11	1.00	0.40	0.46	0.18	-0.07	-0.14	0.34	0.51	0.49	0.35	-0.07	0.42
SOP	0.60	0.15	0.42	-0.39	0.40	1.00	0.70	0.58	-0.31	-0.39	0.32	0.30	0.29	0.48	-0.21	0.48
STAT	0.58	0.10	0.34	-0.35	0.46	0.70	1.00	0.62	-0.35	-0.34	0.32	0.40	0.32	0.59	-0.29	0.44
RSE	0.40	0.15	0.35	-0.62	0.18	0.58	0.62	1.00	-0.50	-0.27	0.45	0.35	0.38	0.63	-0.37	0.39
AEQ	-0.36	0.10	-0.14	0.22	-0.07	-0.31	-0.35	-0.50	1.00	0.57	-0.09	0.08	0.05	-0.61	0.56	-0.23
ERQS	-0.36	-0.04	-0.22	-0.07	-0.14	-0.39	-0.34	-0.27	0.57	1.00	-0.01	-0.10	0.03	-0.44	0.11	-0.27
ERQR	0.25	0.32	0.12	-0.36	0.34	0.32	0.32	0.45	-0.09	-0.01	1.00	0.59	0.71	0.24	0.08	0.39
ERQAP	0.14	0.31	0.31	-0.13	0.51	0.30	0.40	0.35	0.08	-0.10	0.59	1.00	0.54	0.13	0.26	0.46
ERQAV	0.21	0.20	0.31	-0.34	0.49	0.29	0.32	0.38	0.05	0.03	0.71	0.54	1.00	0.21	0.19	0.31
AUTH	0.45	0.03	0.28	-0.40	0.35	0.48	0.59	0.63	-0.61	-0.44	0.24	0.13	0.21	1.00	-0.40	0.49
FNE	-0.34	0.39	0.01	0.21	-0.07	-0.21	-0.29	-0.37	0.56	0.11	0.08	0.26	0.19	-0.40	1.00	0.05
ISEL	0.34	0.38	0.44	-0.30	0.42	0.48	0.44	0.39	-0.23	-0.27	0.39	0.46	0.31	0.49	0.05	1.00

Descriptive Statistics: Experience Sampling Questionnaire

Measure	Mean	SD	Range
Self-Ratings			
Extraversion (2-item)	2.8	1.3	1 - 5
Agreeableness (2-item)	3.6	.84	1 - 5
Conscientiousness (2-item)	3.7	.86	1 - 5
Openness	3.0	1.3	1 - 5
Self-Esteem	3.0	1.1	1 - 5
Fear of Negative Evaluations	2.0	1.2	1 - 5
Power	2.6	1.2	1 - 5
Status	2.5	1.2	1 - 5
Class	2.4	1.2	1 - 5
Reappraisal	2.5	1.2	1 - 5
Suppression	3.2	1.3	1 - 5
Situation Selection (Approach)	2.2	1.2	1 - 5
Situation Selection (Avoid)	2.2	1.2	1 - 5
Ratings of Others			
Extraversion	3.6	1.1	1 - 5
Self-Esteem	3.7	.89	1 - 5
Status	3.4	1.0	1 - 5
Power	3.3	1.0	1 - 5
Class	3.0	1.0	1 - 5

Suppression	3.7	1.0	1 - 5
Closeness	3.7	1.3	1 - 5

Zero-Order Correlations Among Experience Sampling Measures

	s.E	s.A	s.C	s.o	s.sise	s.fne	s.pow	s.stat	s.clas	s.rea	s.sitA	s.sup	s.sitI
s.E	1.00	0.49	0.26	0.50	0.49	-0.06	0.43	0.49	0.38	0.09	0.23	-0.41	-0.15
s.A	0.49	1.00	0.25	0.39	0.37	-0.12	0.28	0.34	0.27	0.06	0.11	-0.22	-0.13
s.C	0.26	0.25	1.00	0.36	0.34	-0.12	0.23	0.23	0.13	0.11	-0.03	-0.16	-0.18
s.o	0.50	0.39	0.36	1.00	0.52	0.07	0.44	0.44	0.40	0.25	0.29	-0.35	0.04
s.sise	0.49	0.37	0.34	0.52	1.00	-0.16	0.57	0.59	0.54	0.16	0.21	-0.38	-0.03
s.fne	-0.06	-0.12	-0.12	0.07	-0.16	1.00	0.04	0.02	0.05	0.32	0.23	-0.02	0.35
s.pow	0.43	0.28	0.23	0.44	0.57	0.04	1.00	0.72	0.65	0.32	0.35	-0.38	0.11
s.stat	0.49	0.34	0.23	0.44	0.59	0.02	0.72	1.00	0.77	0.28	0.39	-0.49	0.08
s.clas	0.38	0.27	0.13	0.40	0.54	0.05	0.65	0.77	1.00	0.30	0.36	-0.42	0.11
s.rea	0.09	0.06	0.11	0.25	0.16	0.32	0.32	0.28	0.30	1.00	0.42	-0.23	0.34
s.sitA	0.23	0.11	-0.03	0.29	0.21	0.23	0.35	0.39	0.36	0.42	1.00	-0.31	0.37
s.sup	-0.41	-0.22	-0.16	-0.35	-0.38	-0.02	-0.38	-0.49	-0.42	-0.23	-0.31	1.00	-0.04
s.sitI	-0.15	-0.13	-0.18	0.04	-0.03	0.35	0.11	0.08	0.11	0.34	0.37	-0.04	1.00

Sample C

Data Cleaning:

Step 1: Merge together separate ESM time-points and re-label variables.

Step 2: Remove Duplicated Rows

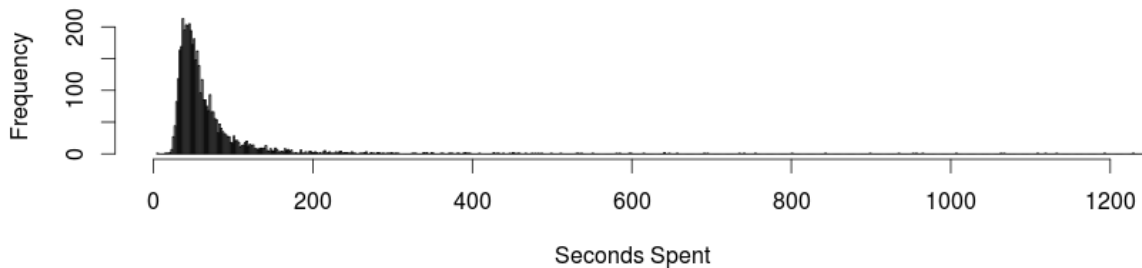
- Duplicates due to the following:
 - a) Errors in online submission.
 - b) Merging in R
 - c) Participant re-submissions (novelty; show to friend) → First submission used.
- 105 duplicate responses removed

Data Filtering:

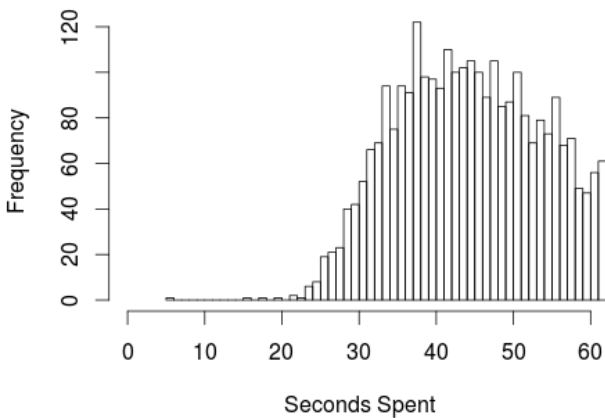
Step 1: Filter by time spent on response (in seconds)

- Mean = 106.4 sec; Median = 53 sec; 50% between 41 and 74 sec.; Max = 25850 sec.
- Fleeson: Exclude > .5 seconds *per item*.
- *Inclusion Criteria: > 20 seconds & < 600 seconds → 77 responses deleted.*

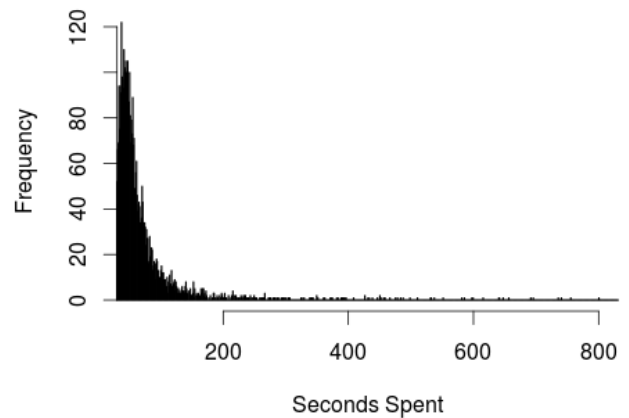
Histogram of ESM Response Time



Histogram of Response Time (Lower Tail)



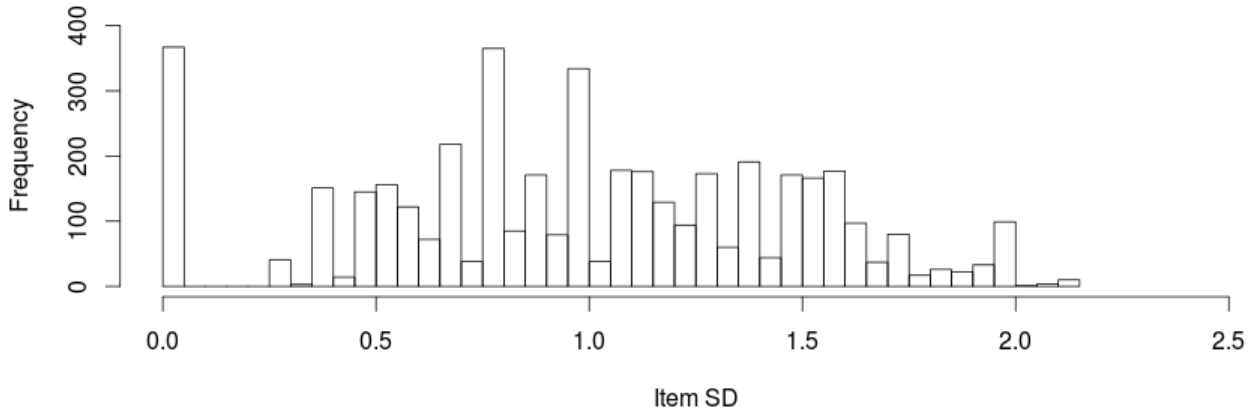
Histogram of Response Time (Upper Tail)



Step 2: Filter by responses with low standard deviation.

- Mean = 1.09, Median = 1.07; Range = 0 - 2.29; 50% Between .77 and 1.41.
- Fleeson: Exclude when 90% of responses are identical.
- *Inclusion Criteria: SD > 0 → 368 responses deleted (361 responses in addition to last filter)*

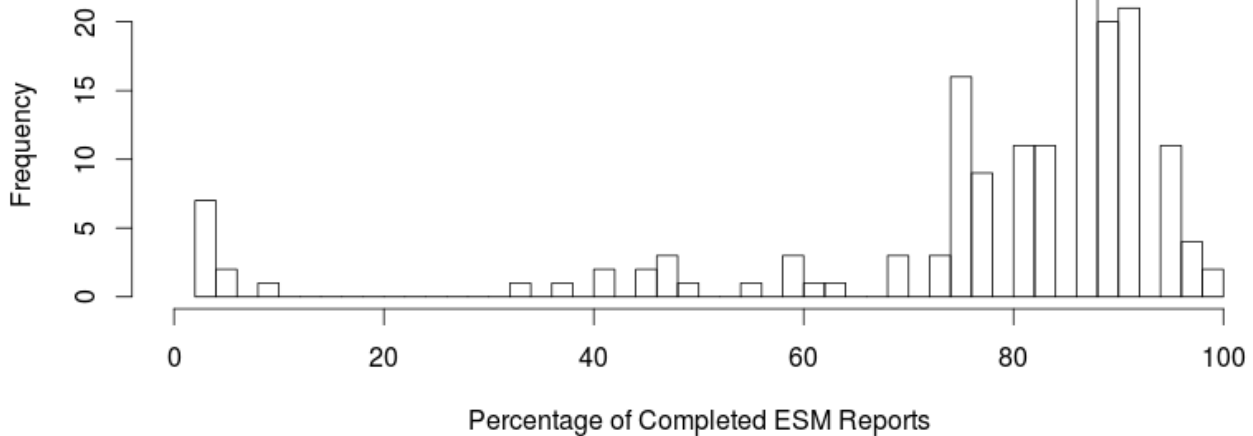
Histogram of SD within Survey (Across Items)



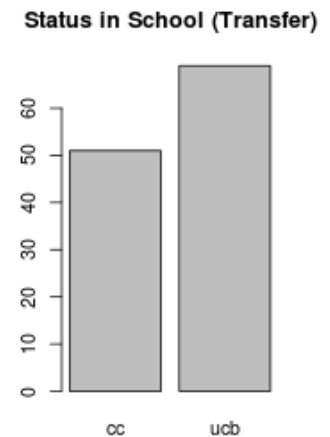
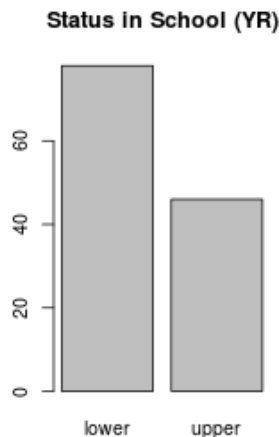
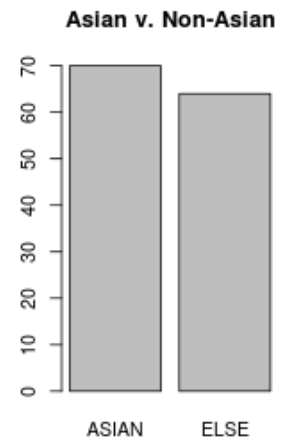
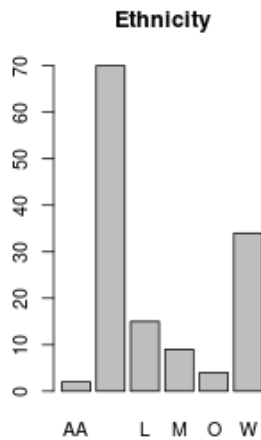
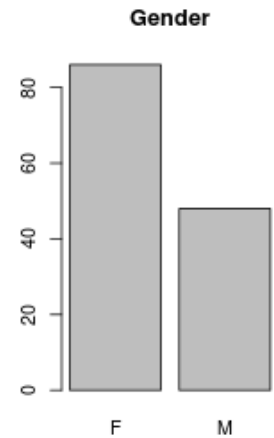
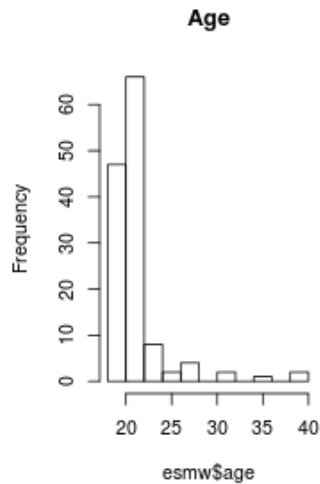
Step 3: Filter by participants with low completion rate.

- Mean = 76.6; Median = 86.1; 50% between 75 and 88.9; Range 2.8 - 100.
- Fleeson: N/A
- *My inclusion: Greater than 40% → 12 participants removed.*

Histogram of Participant Completion Rates



- Wave 1 N = 164 Participants
- Wave 2 N = 154 Participants
- Wave 3 N = 140 Participants
- Age:
 - Mean = 21.74
 - Median = 21
 - Range = 19 - 40
 - SD = 3.14
 - NA = 7
 - ** Participants over the age of 30 removed (N = 134)
 - Mean = 21
 - Median = 21
 - Range = 19-28
 - SD = 1.7
- Sex
 - Male = 46 (34%)
 - Female = 83 (62%)
 - NA = 5
- Ethnicity - **Asian v. Non-Asian**
 - 34 White (25%)
 - 2 Black (1%)
 - 13 Latino (10%)
 - 69 Asian (51%)
 - 9 Middle Eastern (7%)
 - 2 Other (1%)
 - 5 NA (4%)
- Year in School - **Upper v. Lower**
 - Sophomore = 3
 - Junior = 87
 - Senior = 45
 - 5th Year = 8
 - 6th Year = 1
 - N/A = 23
- Transfer Student - **CC vs. UCB**
 - No = 69
 - Yes, CC = 46
 - NA = 19



Descriptive Statistics

Table 1: Descriptive Statistics for Scale Variables

	Raw Alpha	Std. Alpha	Mean	SD
BFIE	0.88	0.88	4.16	1.20
BFIA	0.85	0.85	4.96	1.13
BFIC	0.82	0.83	4.57	1.07
BFIN	0.85	0.85	3.85	1.15
BFIO	0.81	0.82	4.66	1.06
PA	0.90	0.90	4.49	1.30
NA	0.91	0.91	3.05	1.26
ERQSUP	0.81	0.80	3.44	1.38
ERQREA	0.91	0.91	4.46	1.40
ERQSIT	0.67	0.68	4.00	1.08
CAPSUP	0.76	0.77	4.34	1.65
CAPREA	0.90	0.90	4.52	1.66
CAPSIT	0.85	0.85	4.72	1.64
SOP	0.87	0.87	3.80	0.86
STAT	0.93	0.93	4.45	1.29
RSE	0.91	0.91	4.19	0.92
GSE	0.94	0.94	4.95	1.33
FNE	0.80	0.80	3.66	1.30
AEQ	0.93	0.93	3.93	1.49
AUTH	0.80	0.81	3.95	1.27
ISEL	0.91	0.92	3.88	1.20

R Code: Data Cleaning - Sample A

```
## Steps not completed in R

## check for misspelled SIDs
## delete single / researcher responses (ADC / GOMI / TEST)
## use IP to fill-in missing SIDs
## check for misspelled oIDs

## Libraries

library(lme4)
library(psych)
library(chron)

## Load data
setwd('~Downloads/Dropbox/Research/Dissertation/V3/')
data <- read.csv('ESM_v3_021015_IDclean.csv')

## Remove and Rename variables.

## done in excel.

## CREATE NEW VARIABLES

## TIME SPENT ON SURVEY

time.spent <- as.numeric((as.POSIXlt(data$end) - as.POSIXlt(data$start)))
data$time.sec <- time.spent/60

summary(data$time.sec)
sd(data$time.sec)

## ASSESSMENT NUMBER (TIME)

# Create time variables.

time.frame <- t(as.data.frame(strsplit(as.character(data$start), ' ')))

data$time.date <- chron(time.frame[,1], time.frame[,2], format = c(dates = 'y-m-d', times = 'h:m:s'))
data$time.days <- as.numeric(as.factor(as.numeric(days(data$time.date)))) # assessment day
data$time.hour <- as.numeric(hours(data$time.date)) # assessment hour

hist(as.numeric(data$time.date), breaks = 100,
      col = 'black', border = 'white') # XXX: Relabel X values.

hist(data$time.days, xlim = c(1,6), breaks = 24,
      col = 'black', border = 'white')

hist(data$time.hour, breaks = 24, xlim = c(8,24),
      col = 'black', border = 'white')

## ESM Data Filter

## FILTER by three times the sd for time spent.

dataX1 <- subset(data, data$time.sec < (mean(data$time.sec) + 3* sd(data$time.sec)))
```



```

nrow(data) - nrow(dataX1) # 11 rows removed.

## 2. filter by responses with low SD.

colnames(dataX1)
dataX1 <- transform(dataX1, sd.response=apply(dataX1[,10:21], 1, sd, na.rm = TRUE))
summary(dataX1$sd.response)
hist(dataX1$sd.response, breaks = 30)
dataX2 <- subset(dataX1, dataX1$sd.response > .01)

hist(dataX2$sd.response, breaks = 30) # better

## Step 3. filter by % completed.

complete <- stats::aggregate.formula(time.date ~ sid, dataX2, length)

complete$completed <- complete$time.date

summary(complete$completed/.36)

hist((complete$completed), breaks = 40, xlim = c(0, 36),
     xlab = "Percentage of Completed ESM Reports",
     main = "Histogram of Participant Completion Rates")

#comp.filt <- subset(complete, completed >= 14) # only ppts who completed 40% or more.
#comp.filt
#comp.filt <- comp.filt[,-2]

complete <- complete[,-2]

dataX3 <- merge(dataX2, complete, by = "sid")
nrow(dataX3) - nrow(dataX2)

summary(dataX3$completed)

dataX3F <- subset(dataX3, completed >=14)
nrow(dataX3F) - nrow(dataX3)

dataX3F$sid <- as.factor(as.character(dataX3F$sid))

length(levels(dataX3F$sid)) - length(levels(dataX3$sid))

dataX3F$IDX <- as.factor(as.numeric(as.factor(dataX3F$sid)))
write.csv(dataX3F, 'esm_V3_filtered.csv', row.names = F)

####
#####
## Create full time frame.

data <- read.csv('esm_V3_filtered.csv')

#0. Create assessment number for each participant
summary(as.factor(data$time.days)) # day of assessment
summary(as.factor(data$time.hour)) # time of assessment

# combine day and time;

```

```

data$code <- paste(as.factor(as.character(data$time.days)), as.factor(as.character(data$time.hour)), sep = '')
data$code <- as.factor(paste(data$time.days, data$time.hour, sep = ''))
code <- data$code

length(code) # check to make sure same length as data frame.

code.time <- as.character(code)
summary(as.factor(as.numeric(as.character(code)))) # orders the codes
code.time[code.time == "110"] <- 1
code.time[code.time == "111"] <- 1
code.time[code.time == "112"] <- 2
code.time[code.time == "113"] <- 2
code.time[code.time == "114"] <- 3
code.time[code.time == "115"] <- 3
code.time[code.time == "116"] <- 4
code.time[code.time == "117"] <- 4
code.time[code.time == "118"] <- 5
code.time[code.time == "119"] <- 5
code.time[code.time == "120"] <- 6
code.time[code.time == "121"] <- 6
code.time[code.time == "122"] <- 6
code.time[code.time == "123"] <- 6

code.time[code.time == "210"] <- 7
code.time[code.time == "211"] <- 7
code.time[code.time == "212"] <- 8
code.time[code.time == "213"] <- 8
code.time[code.time == "214"] <- 9
code.time[code.time == "215"] <- 9
code.time[code.time == "216"] <- 10
code.time[code.time == "217"] <- 10
code.time[code.time == "218"] <- 11
code.time[code.time == "219"] <- 11
code.time[code.time == "220"] <- 12
code.time[code.time == "221"] <- 12
code.time[code.time == "222"] <- 12
code.time[code.time == "223"] <- 12
code.time[code.time == "38"] <- 12
code.time[code.time == "39"] <- 12

code.time[code.time == "310"] <- 13
code.time[code.time == "311"] <- 13
code.time[code.time == "312"] <- 14
code.time[code.time == "313"] <- 14
code.time[code.time == "314"] <- 15
code.time[code.time == "315"] <- 15
code.time[code.time == "316"] <- 16
code.time[code.time == "317"] <- 16
code.time[code.time == "318"] <- 17
code.time[code.time == "319"] <- 17
code.time[code.time == "320"] <- 18
code.time[code.time == "321"] <- 18
code.time[code.time == "322"] <- 18
code.time[code.time == "323"] <- 18
code.time[code.time == "40"] <- 18
code.time[code.time == "48"] <- 18

code.time[code.time == "410"] <- 19
code.time[code.time == "411"] <- 19

```

```

code.time[code.time == "412"] <- 20
code.time[code.time == "413"] <- 20
code.time[code.time == "414"] <- 21
code.time[code.time == "415"] <- 21
code.time[code.time == "416"] <- 22
code.time[code.time == "417"] <- 22
code.time[code.time == "418"] <- 23
code.time[code.time == "419"] <- 23
code.time[code.time == "420"] <- 24
code.time[code.time == "421"] <- 24
code.time[code.time == "422"] <- 24
code.time[code.time == "423"] <- 24
code.time[code.time == "50"] <- 24
code.time[code.time == "53"] <- 24

code.time[code.time == "510"] <- 25
code.time[code.time == "511"] <- 25
code.time[code.time == "512"] <- 26
code.time[code.time == "513"] <- 26
code.time[code.time == "514"] <- 27
code.time[code.time == "515"] <- 27
code.time[code.time == "516"] <- 28
code.time[code.time == "517"] <- 28
code.time[code.time == "518"] <- 29
code.time[code.time == "519"] <- 29
code.time[code.time == "520"] <- 30
code.time[code.time == "521"] <- 30
code.time[code.time == "522"] <- 30
code.time[code.time == "523"] <- 30
code.time[code.time == "60"] <- 30
code.time[code.time == "61"] <- 30
code.time[code.time == "69"] <- 30

code.time[code.time == "610"] <- 31
code.time[code.time == "611"] <- 31
code.time[code.time == "612"] <- 32
code.time[code.time == "613"] <- 32
code.time[code.time == "614"] <- 33
code.time[code.time == "615"] <- 33
code.time[code.time == "616"] <- 34
code.time[code.time == "617"] <- 34
code.time[code.time == "618"] <- 35
code.time[code.time == "619"] <- 35
code.time[code.time == "620"] <- 36
code.time[code.time == "621"] <- 36
code.time[code.time == "622"] <- 36
code.time[code.time == "623"] <- 36
code.time[code.time == "70"] <- 36
code.time[code.time == "75"] <- 36
code.time[code.time == "710"] <- 36

length(levels(as.factor(code.time))) # got all the possible time combinations.
data$code.time <- as.numeric(code.time)
hist(data$code.time)
data$idx <- as.factor(as.character(as.numeric(data$sid)))

time.frame <- data.frame(idx = rep(1:length(levels(data$idx)), each = 36),
                        code.time = rep(1:36))

```

```

data2 <- merge(data, time.frame, by = c('idx', 'code.time'), all.y = T)
nrow(data2) - sum(duplicated(cbind(data2$idx, data2$code.time))) # some duplicates.

data3 <- data2[duplicated(cbind(data2$idx, data2$code.time)) == F,]

with(data2[data2$idx=='1',], cbind(idx, code.time, time.days, time.hour))
with(data3[data2$idx=='1',], cbind(idx, code.time, time.days, time.hour))

as.factor(data3$idx)

write.csv(data3, 'esm_V3_filtered_expandedTimeCode.csv')
names(data3)
data3$code.time

#####
# GRAPHS

# Filter by time to complete; before/after:

hist(data$time.sec, breaks = 1000) # BEFORE: filtered by timestamp
hist(dataX3F$time.sec, breaks = 1000) # AFTER: filtered by timestamp

# Filter by SD, before/after:

hist(dataX1$sd.response, breaks = 50, # BEFORE: filtering by SD
      main = "Histogram of SD within Survey (Across Items)",
      xlab = "Item SD", ylim = c(0,400))

hist(dataX3F$sd.response, breaks = 50,
      xlab = "Item SD")

## Filter by % completed; before / after:

hist((complete$completed/.36), breaks = 20, xlim = c(0, 120),
      xlab = "Percentage of Completed ESM Reports",
      main = "Histogram of Participant Completion Rates")

hist((dataX3F$completed/.36), breaks = 20, xlim = c(0,120),
      xlab = "Percentage of Completed ESM Reports",
      main = "Histogram of Sample 1 Completion")

#####
## MERGE AND DE-IDENTIFY

self <- read.csv('v3_self_deID_clean.csv')
data <- read.csv('esm_V3_filtered_expandedTimeCode.csv.csv')
names(data)
names(self)

## match SID misspellings / capitalizations
levels(data$sid)
levels(self$sid)
levels(self$sid)[1] <- NA
levels(self$sid)[4] <- "ac1111"
levels(self$sid)[6] <- "AJ0429"
levels(self$sid)[9] <- "Aw0209"

```

```

levels(self$ssid)[11] <- "bk0317"
levels(self$ssid)[14] <- "CG0819"
levels(self$ssid)[17] <- "dq0504"
levels(self$ssid)[20] <- "ES0416"
levels(self$ssid)[23] <- "GP0525"
levels(self$ssid)[26] <- "HG0723"
levels(self$ssid)[34] <- "JK0301"
levels(self$ssid)[36] <- "js310"
levels(self$ssid)[38] <- "LC0320"
levels(self$ssid)[39] <- "LL1021"
levels(self$ssid)[50] <- "RL0413"
levels(self$ssid)[51] <- "RM0123"
levels(self$ssid)[52] <- "Rzs1012"
levels(self$ssid)[54] <- "sr0602"
levels(self$ssid)[56] <- "STY0612"
levels(self$ssid)[60] <- "tg0130"
levels(self$ssid)[61] <- "TH0428"
levels(self$ssid)[62] <- "TT0726"

## merge it.
nrow(data)
nrow(self)
woop <- merge(data, self, by.X = 'sid', all.x = T, all.y = F)
nrow(woop)
length(levels(woop$ssid))
length(levels(data$ssid))

woop$IDX <- as.factor(as.numeric(woop$ssid))
names(woop[,-c(1,2)])

write.csv(woop[,-c(1,2)], 'esm_V3_all_clean_deID.csv', row.names = F)

```

R Code: Data Cleaning - Sample B

```
## Steps not completed in R

## check for misspelled SIDs
## delete single / researcher responses (ADC / GOMI / TEST)
## use IP to fill-in missing SIDs
## check for misspelled oIDs

## Load data

setwd('~/.Dropbox/Research/Dissertation/V2/data/')
d2x <- read.csv('ESM_S2_clean_10152014.csv')

## Load Libraries
library(chron)

## Remove and Rename variables.

d2x <- d2x[,-2]
colnames(d2x) <- c("IP", "start", "end", "sid", "sit", "emo", "int", "val", "numsoc",
                  "s.e", "s.a", "s.c", "s.o",
                  "s.eR", "s.aR", "s.cR", "s.sise",
                  "s.fne", "s.pow", "s.stat", "s.clas",
                  "s.rea", "s.sitA", "s.sup", "s.sitI",
                  "oid", "rel", "o.ext", "o.sise", "o.stat",
                  "o.close", "o.sup", "o.pow", "o.clas")

d2x$s.sup <- 6 - d2x$s.sup # suppression item was reverse coded.

names(d2x)

## CREATE NEW VARIABLES

# Number of People Interacting

names(d2x)
d2x$socF <- d2x$numsoc
d2x$socF[d2x$socF == 1] <- "NA"
d2x$socF[d2x$socF == 2] <- "alone"
d2x$socF[d2x$socF == 3] <- "1"
d2x$socF[d2x$socF == 4] <- "2"
d2x$socF[d2x$socF == 5] <- "3-4"
d2x$socF[d2x$socF == 6] <- "5-10"
d2x$socF[d2x$socF == 7] <- "11-20"
d2x$socF[d2x$socF == 8] <- "20+"
d2x$socF <- as.factor(as.character(d2x$socF))

d2x$socF <- factor(d2x$socF, levels(d2x$socF)[c(7,1,3,5,6,2,4)])
plot(d2x$socF)

# Situations.

names(d2x)

d2x$doF <- d2x$sit
```

```
summary(as.factor(d2x$doF))
```

```
d2x$doF[d2x$doF == 1] <- NA
d2x$doF[d2x$doF == 2] <- "commute"
d2x$doF[d2x$doF == 3] <- "cook.eat"
d2x$doF[d2x$doF == 4] <- "exercize"
d2x$doF[d2x$doF == 5] <- "arguing"
d2x$doF[d2x$doF == 6] <- "grooming"
d2x$doF[d2x$doF == 7] <- "hanging"
d2x$doF[d2x$doF == 8] <- "housework"
d2x$doF[d2x$doF == 9] <- "in.meeting"
d2x$doF[d2x$doF == 10] <- "listen.music"
d2x$doF[d2x$doF == 11] <- "online.social"
d2x$doF[d2x$doF == 12] <- "offline.comp"
d2x$doF[d2x$doF == 13] <- "mobile"
d2x$doF[d2x$doF == 14] <- "outdoors"
d2x$doF[d2x$doF == 15] <- "playing"
d2x$doF[d2x$doF == 16] <- "praying"
d2x$doF[d2x$doF == 17] <- "reading"
d2x$doF[d2x$doF == 18] <- "relaxing"
d2x$doF[d2x$doF == 19] <- "shopping"
d2x$doF[d2x$doF == 20] <- "sleeping"
d2x$doF[d2x$doF == 21] <- "studying"
d2x$doF[d2x$doF == 22] <- "talking"
d2x$doF[d2x$doF == 23] <- "walking"
d2x$doF[d2x$doF == 24] <- "tv.watch"
d2x$doF[d2x$doF == 25] <- "working"
d2x$doF[d2x$doF == 26] <- "other"
d2x$doF[d2x$doF == 27] <- "internet"
```

```
plot(as.factor(d2x$doF))
```

```
d2x$emoF <- d2x$emo
d2x$emoF[d2x$emoF == 3] <- 'accomplished'
d2x$emoF[d2x$emoF == 4] <- NA
d2x$emoF[d2x$emoF == 5] <- 'afraid'
d2x$emoF[d2x$emoF == 6] <- 'amused'
d2x$emoF[d2x$emoF == 7] <- 'angry'
d2x$emoF[d2x$emoF == 8] <- 'annoyed'
d2x$emoF[d2x$emoF == 9] <- 'anxious'
d2x$emoF[d2x$emoF == 10] <- 'arrogant'
d2x$emoF[d2x$emoF == 11] <- 'ashamed'
d2x$emoF[d2x$emoF == 12] <- 'bored'
d2x$emoF[d2x$emoF == 13] <- 'calm'
d2x$emoF[d2x$emoF == 14] <- 'confident'
d2x$emoF[d2x$emoF == 15] <- 'confused'
d2x$emoF[d2x$emoF == 16] <- 'contempt'
d2x$emoF[d2x$emoF == 17] <- 'determined'
d2x$emoF[d2x$emoF == 18] <- 'disgust'
d2x$emoF[d2x$emoF == 19] <- 'dismissive'
d2x$emoF[d2x$emoF == 20] <- 'embarrassed'
d2x$emoF[d2x$emoF == 21] <- 'excited'
d2x$emoF[d2x$emoF == 22] <- 'focused'
d2x$emoF[d2x$emoF == 23] <- 'frustrated'
d2x$emoF[d2x$emoF == 24] <- 'grateful'
d2x$emoF[d2x$emoF == 25] <- 'guilty'
d2x$emoF[d2x$emoF == 26] <- 'happy'
d2x$emoF[d2x$emoF == 27] <- 'inspired'
d2x$emoF[d2x$emoF == 28] <- 'interested'
```

```

d2x$emoF[d2x$emoF == 29] <- 'jealous'
d2x$emoF[d2x$emoF == 30] <- 'lonely'
d2x$emoF[d2x$emoF == 31] <- 'loving'
d2x$emoF[d2x$emoF == 32] <- 'sad'
d2x$emoF[d2x$emoF == 33] <- 'superior'
d2x$emoF[d2x$emoF == 34] <- 'surprised'
d2x$emoF[d2x$emoF == 35] <- 'sympathetic'
d2x$emoF[d2x$emoF == 36] <- 'tired'
d2x$emoF <- as.factor(d2x$emoF)

```

```

plot(d2x$emoF)
summary(d2x$emoF)

```

```

## Intensity

```

```

names(d2x)
d2x$eInt <- d2x$int

```

```

d2x$eInt[d2x$eInt == 1] <- NA
d2x$eInt[d2x$eInt == 2] <- '0'
d2x$eInt[d2x$eInt == 3] <- '1'
d2x$eInt[d2x$eInt == 4] <- '2'
d2x$eInt[d2x$eInt == 5] <- '3'
d2x$eInt[d2x$eInt == 6] <- '4'
d2x$eInt[d2x$eInt == 7] <- '5'
d2x$eInt[d2x$eInt == 8] <- '6'
d2x$eInt[d2x$eInt == 9] <- '7'
d2x$eInt[d2x$eInt == 10] <- '8'
d2x$eInt[d2x$eInt == 11] <- '9'
d2x$eInt[d2x$eInt == 12] <- '10'

```

```

d2x$eInt <- as.numeric(d2x$eInt)

```

```

## Valence

```

```

names(d2x)
d2x$eVal <- d2x$val

```

```

d2x$eVal[d2x$eVal == 1] <- NA
d2x$eVal[d2x$eVal == 2] <- '0'
d2x$eVal[d2x$eVal == 3] <- '1'
d2x$eVal[d2x$eVal == 4] <- '2'
d2x$eVal[d2x$eVal == 5] <- '3'
d2x$eVal[d2x$eVal == 6] <- '4'
d2x$eVal[d2x$eVal == 7] <- '5'
d2x$eVal[d2x$eVal == 8] <- '6'
d2x$eVal[d2x$eVal == 9] <- '7'
d2x$eVal[d2x$eVal == 10] <- '8'
d2x$eVal[d2x$eVal == 11] <- '9'
d2x$eVal[d2x$eVal == 12] <- '10'

```

```

d2x$eVal <- as.numeric(d2x$eVal)

```

```

## Relationship Type

```

```

names(d2x)
d2x$relF <- d2x$rel

```

```

d2x$relF[d2x$relF == 1] <- NA
d2x$relF[d2x$relF == 2] <- 'family'
d2x$relF[d2x$relF == 3] <- 'romantic'

```



```

d2x$relF[d2x$relF == 4] <- 'colleague'
d2x$relF[d2x$relF == 5] <- 'boss'
d2x$relF[d2x$relF == 6] <- 'employee'
d2x$relF[d2x$relF == 7] <- 'stranger'
d2x$relF[d2x$relF == 8] <- 'friend/student'
d2x$relF[d2x$relF == 9] <- 'close friend'

## TIME SPENT ON SURVEY

time.spent <- as.numeric((as.POSIXlt(d2x$end) - as.POSIXlt(d2x$start)))
d2x$time.min <- time.spent/60

summary(d2x$time.min)
range(d2x$time.min)
sd(d2x$time.min)

hist(d2x$time.min, xlim = c(0,5), breaks = 10000)

## ASSESSMENT NUMBER (TIME)

# Create time variables.

time.frame <- t(as.data.frame(strsplit(as.character(d2x$start), ' ')))

d2x$time.date <- chron(time.frame[,1], time.frame[,2], format = c(dates = 'y-m-d', times = 'h:m:s'))
d2x$time.days <- as.numeric(as.factor(as.numeric(days(d2x$time.date)))) # assessment day
d2x$time.hour <- as.numeric(hours(d2x$time.date)) # assessment hour

## ESM Data Filter

## FILTER by three times the sd for time spent.

summary(d2x$time.min)
d2X1 <- subset(d2x, d2x$time.min < (mean(d2x$time.min, na.rm = T) + 3* sd(d2x$time.min, na.rm = T)))
d2X1 <- subset(d2X1, d2X1$time.min > .5)

nrow(d2x) - nrow(d2X1) # 15 assessments removed.
length(levels(d2x$sid)) - length(levels(as.factor(as.character(d2X2$sid)))) # no participants removed

## 2. filter by responses with low SD.

d2X1 <- transform(d2X1, sd.response=apply(d2X1[,10:25], 1, sd, na.rm = TRUE))
summary(d2X1$sd.response)
sd(d2X1$sd.response)
range(d2X1$sd.response)
d2X2 <- subset(d2X1, d2X1$sd.response > .01)

nrow(d2X2) - nrow(d2X1)
length(levels(as.factor(as.character(d2X2$sid)))) - length(levels(as.factor(as.character(d2X1$sid))))

## Step 3. filter by % completed.

complete <- stats::aggregate.formula(time.date ~ sid, d2X2, length)

complete$completed <- complete$time.date

summary(complete$completed/.36)
sd(complete$completed/.36)

```

```

range(complete$completed/.36)
#hist((complete$completed/.36), breaks = 20, xlim = c(0, 120),
#      xlab = "Percentage of Completed ESM Reports",
#      main = "Histogram of Participant Completion Rates")

complete <- complete[,-2]

d2X3 <- merge(d2X2, complete, by = "sid")
nrow(d2X3) - nrow(d2X2)

d2X3F <- subset(d2X3, completed >=14)
nrow(d2X3F) - nrow(d2X3)

d2X3F$sid <- as.factor(as.character(d2X3F$sid))
length(levels(d2X3F$sid))

length(levels(d2X3F$sid)) - length(levels(d2X2$sid))
names(d2X3F)

#####
## Create full time frame.
data <- d2X3F
#0. Create assessment number for each participant
summary(as.factor(data$time.days)) # day of assessment
summary(as.factor(data$time.hour)) # time of assessment

# combine day and time;
data$code <- paste(as.factor(as.character(data$time.days)), as.factor(as.character(data$time.hour)), sep = '')
data$code <- as.factor(paste(data$time.days, data$time.hour, sep = ''))
code <- data$code

length(code) # check to make sure same length as data frame.

code.time <- as.character(code)
summary(as.factor(as.numeric(as.character(code)))) # orders the codes
code.time[code.time == "110"] <- 1
code.time[code.time == "111"] <- 1
code.time[code.time == "112"] <- 2
code.time[code.time == "113"] <- 2
code.time[code.time == "114"] <- 3
code.time[code.time == "115"] <- 3
code.time[code.time == "116"] <- 4
code.time[code.time == "117"] <- 4
code.time[code.time == "118"] <- 5
code.time[code.time == "119"] <- 5
code.time[code.time == "120"] <- 6
code.time[code.time == "121"] <- 6
code.time[code.time == "123"] <- 6

code.time[code.time == "210"] <- 7
code.time[code.time == "211"] <- 7
code.time[code.time == "212"] <- 8
code.time[code.time == "213"] <- 8
code.time[code.time == "214"] <- 9
code.time[code.time == "215"] <- 9
code.time[code.time == "216"] <- 10
code.time[code.time == "217"] <- 10
code.time[code.time == "218"] <- 11
code.time[code.time == "219"] <- 11

```

```
code.time[code.time == "220"] <- 12
code.time[code.time == "221"] <- 12
code.time[code.time == "222"] <- 12
code.time[code.time == "223"] <- 12
code.time[code.time == "38"] <- 12
code.time[code.time == "39"] <- 12

code.time[code.time == "310"] <- 13
code.time[code.time == "311"] <- 13
code.time[code.time == "312"] <- 14
code.time[code.time == "313"] <- 14
code.time[code.time == "314"] <- 15
code.time[code.time == "315"] <- 15
code.time[code.time == "316"] <- 16
code.time[code.time == "317"] <- 16
code.time[code.time == "318"] <- 17
code.time[code.time == "319"] <- 17
code.time[code.time == "320"] <- 18
code.time[code.time == "321"] <- 18
code.time[code.time == "322"] <- 18
code.time[code.time == "323"] <- 18
code.time[code.time == "40"] <- 18

code.time[code.time == "410"] <- 19
code.time[code.time == "411"] <- 19
code.time[code.time == "412"] <- 20
code.time[code.time == "413"] <- 20
code.time[code.time == "414"] <- 21
code.time[code.time == "415"] <- 21
code.time[code.time == "416"] <- 22
code.time[code.time == "417"] <- 22
code.time[code.time == "418"] <- 23
code.time[code.time == "419"] <- 23
code.time[code.time == "420"] <- 24
code.time[code.time == "421"] <- 24
code.time[code.time == "422"] <- 24
code.time[code.time == "423"] <- 24
code.time[code.time == "50"] <- 24

code.time[code.time == "510"] <- 25
code.time[code.time == "511"] <- 25
code.time[code.time == "512"] <- 26
code.time[code.time == "513"] <- 26
code.time[code.time == "514"] <- 27
code.time[code.time == "515"] <- 27
code.time[code.time == "516"] <- 28
code.time[code.time == "517"] <- 28
code.time[code.time == "518"] <- 29
code.time[code.time == "519"] <- 29
code.time[code.time == "520"] <- 30
code.time[code.time == "521"] <- 30
code.time[code.time == "522"] <- 30
code.time[code.time == "523"] <- 30
code.time[code.time == "60"] <- 30
code.time[code.time == "61"] <- 30
code.time[code.time == "69"] <- 30

code.time[code.time == "610"] <- 31
code.time[code.time == "611"] <- 31
```

```

code.time[code.time == "612"] <- 32
code.time[code.time == "613"] <- 32
code.time[code.time == "614"] <- 33
code.time[code.time == "615"] <- 33
code.time[code.time == "616"] <- 34
code.time[code.time == "617"] <- 34
code.time[code.time == "618"] <- 35
code.time[code.time == "619"] <- 35
code.time[code.time == "620"] <- 36
code.time[code.time == "621"] <- 36
code.time[code.time == "622"] <- 36
code.time[code.time == "623"] <- 36
code.time[code.time == "70"] <- 36

data$code.time <- as.numeric(code.time)
data$idx <- as.factor(as.character(as.numeric(data$cid)))
time.frame <- data.frame(idx = rep(1:length(levels(data$idx)), each = 36),
                        code.time = rep(1:36))

data2 <- merge(data, time.frame, by = c('idx', 'code.time'), all.y = T)
nrow(data2) - sum(duplicated(cbind(data2$idx, data2$code.time))) # some duplicates.

data3 <- data2[duplicated(cbind(data2$idx, data2$code.time)) == F,]

with(data2[data2$idx=='1',], cbind(idx, code.time, time.days, time.hour))
with(data3[data3$idx=='1',], cbind(idx, code.time, time.days, time.hour))

as.factor(data3$idx)
write.csv(data3, 'esm_V2_filtered.csv', row.names = F)

#####
## GRAPHS

hist(as.numeric(d2x$time.date), breaks = 100,
     col = 'black', border = 'white') # XXX: Relabel X values.

hist(d2x$time.days, xlim = c(1,6), breaks = 24,
     col = 'black', border = 'white')

hist(d2x$time.hour, breaks = 24, xlim = c(8,24),
     col = 'black', border = 'white')

# Filter by time to complete; before/after:

hist(d2x$time.sec, breaks = 100000) # BEFORE: filtered by timestamp
hist(d2X3F$time.sec, breaks = 1000) # AFTER: filtered by timestamp

# Filter by SD, before/after:

hist(d2X1$sd.response, breaks = 50, # BEFORE: filtering by SD
     main = "Histogram of SD within Survey (Across Items)",
     xlab = "Item SD", ylim = c(0,400))

hist(d2X3F$sd.response, breaks = 500,
     xlab = "Item SD")

## Filter by % completed; before / after:

hist((complete$completed/.36), breaks = 20, xlim = c(0, 120),

```

```
xlab = "Percentage of Completed ESM Reports",  
main = "Histogram of Participant Completion Rates")  
  
hist((d2X3F$completed/.36), breaks = 20, xlim = c(0,120),  
xlab = "Percentage of Completed ESM Reports",  
main = "Histogram of Sample 1 Completion")
```

R Code: Data Cleaning - Sample C

```
# combine power & status

esm <- read.csv("~/Desktop/ESM_merge_test", sep = ";")
names(esm)
corr.test(esm$pow, esm$stat)
corr.test(esm$opow, esm$ostat)
esm$powst <- (esm$pow + esm$ostat)/2
esm$pwst <- (esm$pow + esm$stat)/2
write.csv(esm, "~/Desktop/ESM_merge_test.csv")

## Remove Duplicates

## SORT BY ID, THEN TIME, THEN START.

esmX <- read.csv("~/Desktop/Dissertation/ESM_merge_test.csv", sep = ";")
head(esmX)

length(esmX$ID)

## remove duplicate rows.

any(duplicated(esm[c("ID", "time")])) ## Tests for presence of duplicates.

del.list <- which(duplicated(esm[c("ID", "time")])) ## Finds which rows are dups.
del.list

## Compare dup to pre-dup
esm[del.list, ]
esm[del.list-1, ]

dedup.data <- esm[-del.list, ]
any(duplicated(dedup.data[c("ID", "time")]))

length(esmX$ID) - length(esm$ID)
levels(dedup.data$ID)

write.csv(dedup.data, "~/Desktop/esm_dedup.csv")

## FILTERS:

esm <- read.csv("~/Desktop/esm_dedup.csv")

## 1. filter by time spent on response
par(mfrow = c(1,2))
par(mfrow = c(1,1))
esm$time.spent <- as.numeric(as.POSIXlt(esm$end) - as.POSIXlt(esm$start))
summary(esm$time.spent)

par(mfrow = c(1,1))
hist(esm$time.spent, breaks = 10000, xlim = c(0,1200),
     main = "Histogram of ESM Response Time", xlab = "Seconds Spent")
par(mfrow = c(1,2))
hist(esm$time.spent, xlim = c(0,60), breaks = 30000,
     main = "Histogram of Response Time (Lower Tail)", xlab = "Seconds Spent")
hist(esm$time.spent, xlim = c(60,800), breaks = 30000,
```

```

    main = "Histogram of Response Time (Upper Tail)", xlab = "Seconds Spent")

esmF1 <- subset(esm, time.spent < 500 & time.spent > 20)
hist(esmF1$time.spent, xlim = c(20, 500), breaks = 300)
length(esmF1$ID) - length(esm$ID)

## 2. filter by responses with low SD.

duplicated(esm[,11:23])
esm[1,]
head(esm)
names(esm)
esm <- transform(esm, sd.response=apply(esm[,12:23],1, sd, na.rm = TRUE))
head(esm)
par(mfrow = c(1,1))
hist(esm$sd.response, breaks = 50, main = "Histogram of SD within Survey (Across Items)",
      xlab = "Item SD", ylim = c(0,400), xlim = c(0,2.5))
esmF2 <- subset(esm, esm$sd.response > .01)
length(esmF2$ID) - length(esm$ID)
length(esmF2$ID) - length(esmF1$ID)
length(esmF12$ID) - length(esmF1$ID)

## filter the filtered dataset.
esmF1 <- transform(esmF1, sd.response=apply(esmF1[,12:23],1, sd, na.rm = TRUE))
esmF12 <- subset(esmF1, esmF1$sd.response > .01)
length(esmF12$ID) - length(esm$ID)

## Step 3. filter by % completed.

completed <- aggregate(time ~ ID, esm, length)
summary(completed$time/.36)

hist((completed$time/.36), breaks = 40, xlim = c(0,100),
      xlab = "Percentage of Completed ESM Reports",
      main = "Histogram of Participant Completion Rates")

head(completed)
14/36
comp.filt <- subset(completed, time >= 14)
hist((comp.filt$time/.36), breaks = 10, xlim = c(0,100),
      xlab = "Percentage of Completed ESM Reports",
      main = "Histogram of Sample 1 Completion")

length(comp.filt$ID) - length(levels(esm$ID))

## post-filter filter.
completedF <- aggregate(time ~ ID, esmF12, length)
comp.filt <- subset(completedF, time >= 14)
esmFF <- merge(esmF12, comp.filt, by = "ID")

length(esmFF$ID) - length(esmF12$ID)
length(esmFF$ID) - length(esm$ID)
length(esmFF$ID) / length(esm$ID)

names(esmFF)
colnames(esmFF)[3] <- "time"

```

```

colnames(esmFF)[27] <- "comp"
colnames(esmFF)[26] <- "sd.resp"

write.csv(esmFF, "~/Desktop/esm_pilot_filtered.csv", row.names = F)

## POST FILTER VISUALIZAITONS
par(mfrow = c(1,2))

hist(esm$time.spent, breaks = 6000, xlim = c(0,500), ylim = c(0,500),
     main = "Histogram of Response Time - Un-Filtered", xlab = "Seconds Spent")
hist(esmFF$time.spent, breaks = 100, xlim = c(0,500), ylim = c(0,500),
     main = "Histogram of Response Time - Filtered", xlab = "Seconds Spent")

hist(esm$sd.response, breaks = 50, main = "Histogram of SD Across Items - Un-Filtered",
     xlab = "Item SD", ylim = c(0,400), xlim = c(0,2.5))
hist(esmFF$sd.resp, breaks = 50, main = "Histogram of SD Across Items - Filtered",
     xlab = "Item SD", ylim = c(0,400), xlim = c(0,2.5))

hist((completed$time/.36), breaks = 40, xlim = c(0,100),
     xlab = "Percentage of Completed ESM Reports",
     main = "Histogram of Completion Rates - Un-Filtered")
hist((esmFF$comp/.36), breaks = 40, xlim = c(0,100),
     xlab = "Percentage of Completed ESM Reports",
     main = "Histogram of Completion Rates - Filtered")

## NO NEED TO FILTER?

## 3. filter participants with low total SD.

esm.sd <- aggregate(cbind(feel, social, sup, sit, ext, sise, auth, stat, pow,
                          oext, osize, ostat, opow, opwt, pwst)
                    ~ ID, esm, sd, na.action = "na.pass", na.rm = T)
head(esm.sd)
esm.sd <- transform(esm.sd, sd.t = apply(esm.sd[,2:16],1, mean, na.rm = TRUE))
summary(esm.sd$sd.t)

hist(esm.sd$sd.t, breaks = 40, main = "Histogram of Participant SD Across Items and Surveys",
     xlab = "Standard Deviation", xlim = c(0,1.5))
esm.sdF <- subset(esm.sd, sd.t > .2)
hist(esm.sd$sd.t)

esmF3 <- merge(esm, esm.sdF, by = "ID", all.y = T)

length(esmF3$ID) - length(esm$ID)
length(esmF3$ID) - length(esmF2$ID)

## 3. filter by participants with low response SD.

ppt_respSD <- aggregate(sd.response ~ ID, esmF2, mean)
summary(ppt_respSD$sd.response)
hist(ppt_respSD$sd.response, breaks = 50, main = "Histogram of Ppt's Average Response SD",
     xlab = "Standard Deviation")
ppt_respSDF <- subset(ppt_respSD, ppt_respSD$sd.response > .25)

esmF3 <- merge(esm, ppt_respSDF, by = "ID", all.y = T)
head(esmF3)

length(esmF3$ID) - length(esm$ID)

```



```

length(esmF3$ID) - length(esmF2$ID)

## MERGE PRE-SCREENING & POST-SCREENING
pre <- read.csv("~/Desktop/Dissertation/ESM - Raw Pilot Data/catterson_ESM__PreQuest.csv")
names(pre)

post <- read.csv("~/Desktop/Dissertation/catterson_ESM__PostQuest.csv")
names(post)
length(post$ID)
self.data <- merge(pre, post, by = "student.ID", all.x = T, all.y = T)
write.csv(self.data, "~/Desktop/ESM-self.csv")

#####

## Steps not completed in R

## check for misspelled SIDs
## delete single / researcher responses (ADC / GOMI / TEST)
## use IP to fill-in missing SIDs
## check for misspelled oIDs

## Load data
names(s2)

## CREATE NEW VARIABLES

# Number of People Interacting

names(s2)
hist(s2$social)
s2$socF <- s2$social
s2$socF[s2$socF == 1] <- "alone"
s2$socF[s2$socF == 2] <- "1"
s2$socF[s2$socF == 3] <- "2"
s2$socF[s2$socF == 4] <- "3-4"
s2$socF[s2$socF == 5] <- "5-10"
s2$socF[s2$socF == 6] <- "11-20"
s2$socF[s2$socF == 7] <- "20+"

s2$socF <- as.factor(as.character(s2$socF))
s2$socF <- factor(s2$socF, levels(s2$socF)[c(7,1,3,5,6,2,4)])
plot(s2$socF)

# Situations.

names(s2)

s2$doF <- s2$do
summary(as.factor(s2$doF))

s2$doF[s2$doF == 1] <- 'internet'
s2$doF[s2$doF == 2] <- "commute"
s2$doF[s2$doF == 3] <- "cook.eat"
s2$doF[s2$doF == 4] <- "exercize"
s2$doF[s2$doF == 5] <- "arguing"
s2$doF[s2$doF == 6] <- "grooming"
s2$doF[s2$doF == 7] <- "hanging"
s2$doF[s2$doF == 8] <- "housework"

```

```

s2$doF[s2$doF == 9] <- "in.meeting"
s2$doF[s2$doF == 10] <- "music"
s2$doF[s2$doF == 11] <- "facebook"
s2$doF[s2$doF == 12] <- "offline.comp"
s2$doF[s2$doF == 13] <- "mobile"
s2$doF[s2$doF == 14] <- "outdoors"
s2$doF[s2$doF == 15] <- "playing"
s2$doF[s2$doF == 16] <- "praying"
s2$doF[s2$doF == 17] <- "reading"
s2$doF[s2$doF == 18] <- "relaxing"
s2$doF[s2$doF == 19] <- "shopping"
s2$doF[s2$doF == 20] <- "sleeping"
s2$doF[s2$doF == 21] <- "studying"
s2$doF[s2$doF == 22] <- "talking"
s2$doF[s2$doF == 23] <- "walking"
s2$doF[s2$doF == 24] <- "tv"
s2$doF[s2$doF == 25] <- "working"
s2$doF[s2$doF == 26] <- "other"

plot(as.factor(s2$doF))

## TIME SPENT ON SURVEY

time.spent <- as.numeric((as.POSIXlt(s2$end) - as.POSIXlt(s2$start)))
s2$time.min <- time.spent/60

summary(s2$time.min)
range(s2$time.min)
sd(s2$time.min)

hist(s2$time.min, xlim = c(0,5), breaks = 10000)

## ASSESSMENT NUMBER (TIME)

# Create time variables.

time.frame <- t(as.data.frame(strsplit(as.character(s2$start), ' ')))

s2$time.date <- chron(time.frame[,1], time.frame[,2], format = c(dates = 'y-m-d', times = 'h:m:s'))
s2$time.days <- as.numeric(as.factor(as.numeric(days(s2$time.date)))) # assessment day
s2$time.hour <- as.numeric(hours(s2$time.date)) # assessment hour

## ESM Data Filter

## FILTER by three times the sd for time spent.

summary(s2$time.min)
s21 <- subset(s2, s2$time.min < (mean(s2$time.min, na.rm = T) + 3* sd(s2$time.min, na.rm = T)))
s21 <- subset(s21, s21$time.min > .5)

nrow(s2) - nrow(s21) # 15 assessments removed.
length(levels(s2$sid)) - length(levels(as.factor(as.character(s22$sid)))) # no participants removed

## 2. filter by responses with low SD.

s21 <- transform(s21, sd.response=apply(s21[,10:25], 1, sd, na.rm = TRUE))
summary(s21$sd.response)

```

```

sd(s21$sd.response)
range(s21$sd.response)
s22 <- subset(s21, s21$sd.response > .01)

nrow(s22) - nrow(s21)
length(levels(as.factor(as.character(s22$sid)))) - length(levels(as.factor(as.character(s21$sid))))

## Step 3. filter by % completed.

complete <- stats::aggregate.formula(time.date ~ sid, s22, length)

complete$completed <- complete$time.date

summary(complete$completed/.36)
sd(complete$completed/.36)
range(complete$completed/.36)
#hist((complete$completed/.36), breaks = 20, xlim = c(0, 120),
#      xlab = "Percentage of Completed ESM Reports",
#      main = "Histogram of Participant Completion Rates")

complete <- complete[,-2]

s23 <- merge(s22, complete, by = "sid")
nrow(s23) - nrow(s22)

s23F <- subset(s23, completed >=14)
nrow(s23F) - nrow(s23)

s23F$sid <- as.factor(as.character(s23F$sid))
length(levels(s23F$sid))

length(levels(s23F$sid)) - length(levels(s22$sid))
names(s23F)
write.csv(s23F, 'esm_V2_filtered.csv', row.names = F)

#####
## GRAPHS

hist(as.numeric(s2$time.date), breaks = 100,
     col = 'black', border = 'white') # XXX: Relabel X values.

hist(s2$time.days, xlim = c(1,6), breaks = 24,
     col = 'black', border = 'white')

hist(s2$time.hour, breaks = 24, xlim = c(8,24),
     col = 'black', border = 'white')

# Filter by time to complete; before/after:

hist(s2$time.sec, breaks = 100000) # BEFORE: filtered by timestamp
hist(s23F$time.sec, breaks = 1000) # AFTER: filtered by timestamp

# Filter by SD, before/after:

hist(s21$sd.response, breaks = 50, # BEFORE: filtering by SD
     main = "Histogram of SD within Survey (Across Items)",

```

```

xlab = "Item SD", ylim = c(0,400))

hist(s23F$sd.response, breaks = 500,
     xlab = "Item SD")

## Filter by % completed; before / after:

hist((complete$completed/.36), breaks = 20, xlim = c(0, 120),
     xlab = "Percentage of Completed ESM Reports",
     main = "Histogram of Participant Completion Rates")

hist((s23F$completed/.36), breaks = 20, xlim = c(0,120),
     xlab = "Percentage of Completed ESM Reports",
     main = "Histogram of Sample 1 Completion")

#####
time.frame <- data.frame(idx = rep(1:length(levels(s2$idx)), each = 36),
                        time = rep(1:36))
nrow(time.frame) - length(levels(s2$idx)) * 36 # making sure it is the right length.
head(time.frame)
test <- merge(s2, time.frame, by = c('idx', 'time'), all.y = T)

nrow(test)

head(test)

```

R Code: Chapter Figures and Analyses - Chapter 1

```
## Sample Figures

## FIGURE 1A
high <- c(4,5,6)
low <- c(1,2,3)

barplot(cbind("High Power" = mean(high, na.rm = T),
             "Low Power" = mean(low, na.rm = T)),
        ylim = c(0,7), col = 'black', ylab = "Talkativeness", xlab = "Manipulated Power",
        main = "Fig 1A: Mean-Level Difference")

## FIGURE 1B

ext1 <- c(1,2,3)
plot(low, ext1, xlim = c(0,4), ylim = c(0,4),
     xlab = "Social Power", pch = 19,
     ylab = "Talkativeness",
     main = "Fig 1B: Correlational Relationship")
clip(1,3,1,3)
abline(lm(ext1~low), lwd = 3, col = 'black')

## FIGURE 1C
## DATA FROM CAPITAL_ANALYSES.R
dataex0 <- data[data$idx == 2,] # create subset of ppts for graphing.
dataex1 <- data[data$idx == c(2,3),] # create subset of ppts for graphing.
dataex2 <- data[data$idx == 3,]

fig0ex1 <- ggplot(dataex1, aes(pow, fill = as.factor(idx))) + geom_density(alpha = .1) +
  ylab("Density\n") + xlab("\nSocial Power (Within-Person)") + ylim(0,1.5) + xlim(1,5) +
  theme_tufte(base_size = 10, base_family = 'Ariel') +
  theme(panel.margin = unit(5, "lines")) + guides(fill = F) +
  ggtitle("Fig. 1C: Within-Person Variation") + theme(plot.title = element_text(vjust = 2, face="bold"))
fig1C <- fig0ex1 + geom_vline(xintercept = 4, size = 1.15) +
  geom_vline(xintercept = 2.5, size = 1.15, linetype = 'dashed')
fig1C

?ggtitle
## FIGURE 1D
x11()
ext <- c(1,2,3,0,1,2,1,2,3,2,3,4)
pow <- c(1,2,3,2,1,0,3,2,1,4,3,2)

plot(pow, ext, xlim = c(0,4), ylim = c(0,4),
     xlab = "Social Power", pch = 1,
     ylab = "Talkativeness",
     main = "")
opar <- par(new = TRUE)
plot(low, ext1, xlim = c(0,4), ylim = c(0,4),
     xlab = "", pch = 19,
     ylab = "",
     main = "")
clip(1,3,1,3)
abline(lm(ext1~low), lwd = 3, col = 'black')

clip(0,2,2,0)
abline(a = 2, b = -1, lwd = 3, lty = 'dashed')
```

```

clip(1,3,3,1)
abline(a = 4, b = -1, lwd = 3, lty = 'dashed')

clip(2,4,4,2)
abline(a = 6, b = -1, lwd = 3, lty = 'dashed')

### PUTTING IT ALL TOGETHER

library(gridBase)
x11()
par(mfrow=c(2, 2))
barplot(cbind("High Power" = mean(high, na.rm = T),
             "Low Power" = mean(low, na.rm = T)),
        ylim = c(0,7), col = 'black', ylab = "Talkativeness", xlab = "Manipulated Power",
        main = "Fig. 1A: Mean-Level Difference")

plot(low, ext1, xlim = c(0,4), ylim = c(0,4),
     xlab = "Social Power", pch = 19,
     ylab = "Talkativeness",
     main = "Fig. 1B: Correlational Relationship")
clip(1,3,1,3)
abline(lm(ext1~low), lwd = 3, col = 'black')

plot.new()          ## suggested by @Josh
vps <- baseViewports()
pushViewport(vps$figure) ## I am in the space of the autocorrelation plot
vp1 <-plotViewport(c(1.8,1,1,1)) ## create new vp with margins, you play with this values
acz <- acf(y, plot=F)
acd <- data.frame(lag=acz$lag, acf=acz$acf)
p <- fig1C
plot(pow, ext, xlim = c(0,4), ylim = c(0,4),
     xlab = "Social Power", pch = 1,
     ylab = "Talkativeness",
     main = "Fig. 1D: Between and Within-Person Effects")
opar <- par(new = TRUE)
plot(low, ext1, xlim = c(0,4), ylim = c(0,4),
     xlab = "", pch = 19,
     ylab = "",
     main = "")
clip(1,3,1,3)
abline(lm(ext1~low), lwd = 2, col = 'black')

clip(0,2,2,0)
abline(a = 2, b = -1, lwd = 2, lty = 'dashed')

clip(1,3,3,1)
abline(a = 4, b = -1, lwd = 2, lty = 'dashed')

clip(2,4,4,2)
abline(a = 6, b = -1, lwd = 2, lty = 'dashed')
print(p,vp = vp1)      ## suggested by @bpatiste

#####
fig0ex1 <- ggplot(dataex1, aes(pow, fill = as.factor(idx))) + geom_density(alpha = .1) +
  ylab("Density\n") + xlab("\nSocial Power (Within-Person)") + ylim(0,1.5) + xlim(1,5) +
  theme_tufte(base_size = 12, base_family = 'HersheySans') +
  theme(panel.margin = unit(5, "lines")) + guides(fill = F)
fig1C <- fig0ex1 + geom_vline(xintercept = 4, size = 1.15) +

```

```
  geom_vline(xintercept = 2.5, size = 1.15, linetype = 'dashed')  
x11()  
fig1C
```

R Code: Chapter Figures and Analyses - Chapter 2

```
library(lme4)
library(car)
library(psych)
library(ggplot2)
library(ggthemes)
library(grid)
library(gridExtra)
library(reshape)

set.seed(12345) # ensures reproducibility of bootstrapped results.

## Variance Inflation Factor Function
## Function written by Austin Frank: https://github.com/auf frank/R-hacks/blob/master/mer-utils.R
vif.mer <- function (fit) {
  ## adapted from rms::vif

  v <- vcov(fit)
  nam <- names(fixef(fit))

  ## exclude intercepts
  ns <- sum(1 * (nam == "Intercept" | nam == "(Intercept)"))
  if (ns > 0) {
    v <- v[-(1:ns), -(1:ns), drop = FALSE]
    nam <- nam[-(1:ns)]
  }

  d <- diag(v)^0.5
  v <- diag(solve(v/(d %o% d)))
  names(v) <- nam
  v
}

#####
## LOAD DATA: And some merging / de-identifying      ##
#####

setwd('~/.Dropbox/Research/Dissertation/Chapter: Social Power, Status, and Capital/')

# Sample 1
s1 <- read.csv('data//esm_sample1_deID.csv')
s1S <- read.csv('data//dem_sample1_deID.csv')

# Sample 2

s2 <- read.csv('data//esm_sample2_deID.csv')
s2S <- read.csv('data//dem_sample2_deID.csv')

#####
## Sample Demographics:                                ##
#####

names(s1S)
samp1 <- with(s1S, data.frame(age, sex, eth))
s2S$age[35] <- 22
s2S$age[72] <- 19
s2S$age <- as.numeric(as.character(s2S$age))
```



```

samp2 <- with(s2S, data.frame(age, sex, eth))

summary(samp1) / nrow (samp1)
summary(samp2) / nrow (samp2)

self.data <- rbind(samp1, samp2)
nrow(self.data)

## Merging it together

# make sure IDs don't overlap
levels(as.factor(s1$idx))
s1$idx <- as.factor(s1$idx)
s2$idx <- as.factor(s2$IDX + 57)

# extract variables for shared analysis
names(s1)
s1m <- s1[,c(1, 49:51, 2, 6, 7, 10, 20:22)]
names(s1m) <- c("idx", "age", "sex", "eth", "code.time", "sit", "emo", "numsoc", "pow", "stat", "clas")

names(s2)
s2m <- s2[,c(29, 30:32, 28, 3:4, 7, 13:15)]
names(s2m) <- c("idx", "age", "sex", "eth", "code.time", "sit", "emo", "numsoc", "pow", "stat", "clas")

data <- rbind(s1m, s2m)
names(data)
nrow(data)
length(levels(data$idx))

## Get participant descriptive statistics.

data$sex
data$eth

data$sexN <- as.numeric(data$sex)
data$ethN <- as.numeric(data$eth)

age.X <- (with(data, tapply(age, INDEX = idx, FUN = mean, na.rm = T)))
eth.X <- (with(data, tapply(ethN, INDEX = idx, FUN = mean, na.rm = T)))
sex.X <- (with(data, tapply(sexN, INDEX = idx, FUN = mean, na.rm = T)))

self <- data.frame(age.X, eth.X, sex.X)

self$sex.X <- as.factor(self$sex.X)
levels(self$sex.X) <- c(levels(data$sex), NA)

self$eth.X <- as.factor(self$eth.X)
levels(self$eth.X) <- c(levels(data$eth), NA)

summary(self$age.X)
sd(self$age.X, na.rm = T)
summary(self$sex.X) / nrow(self)
summary(self$eth.X) / nrow(self)

```

```
#####
```

```
## DATA CLEAN: Calculating Situational Variables      ##
#####
```

```
data$doF <- data$sit ##### CHECK THIS FOR EACH SAMPLE, YO!!
```

```
summary(as.factor(data$doF))
```

```
data$doF[data$doF == 1] <- NA
data$doF[data$doF == 2] <- "commute"
data$doF[data$doF == 3] <- "cook.eat"
data$doF[data$doF == 4] <- "exercize"
data$doF[data$doF == 5] <- "arguing"
data$doF[data$doF == 6] <- "grooming"
data$doF[data$doF == 7] <- "hanging"
data$doF[data$doF == 8] <- "housework"
data$doF[data$doF == 9] <- "in.meeting"
data$doF[data$doF == 10] <- "listen.music"
data$doF[data$doF == 11] <- "online.social"
data$doF[data$doF == 12] <- "offline.comp"
data$doF[data$doF == 13] <- "mobile"
data$doF[data$doF == 14] <- "outdoors"
data$doF[data$doF == 15] <- "playing"
data$doF[data$doF == 16] <- "praying"
data$doF[data$doF == 17] <- "reading"
data$doF[data$doF == 18] <- "relaxing"
data$doF[data$doF == 19] <- "shopping"
data$doF[data$doF == 20] <- "sleeping"
data$doF[data$doF == 21] <- "studying"
data$doF[data$doF == 22] <- "talking"
data$doF[data$doF == 23] <- "walking"
data$doF[data$doF == 24] <- "tv.watch"
data$doF[data$doF == 25] <- "working"
data$doF[data$doF == 26] <- "other"
data$doF[data$doF == 27] <- "internet"
data$doF[data$doF == 53] <- "studying"
data$doF <- as.factor(data$doF)
```

```
## Emotion
```

```
data$emoF <- data$emo
data$emoF[data$emoF == 3] <- 'accomplished'
data$emoF[data$emoF == 4] <- NA
data$emoF[data$emoF == 5] <- 'afraid'
data$emoF[data$emoF == 6] <- 'amused'
data$emoF[data$emoF == 7] <- 'angry'
data$emoF[data$emoF == 8] <- 'annoyed'
data$emoF[data$emoF == 9] <- 'anxious'
data$emoF[data$emoF == 10] <- 'arrogant'
data$emoF[data$emoF == 11] <- 'ashamed'
data$emoF[data$emoF == 12] <- 'bored'
data$emoF[data$emoF == 13] <- 'calm'
data$emoF[data$emoF == 14] <- 'confident'
data$emoF[data$emoF == 15] <- 'confused'
data$emoF[data$emoF == 16] <- 'contempt'
data$emoF[data$emoF == 17] <- 'determined'
data$emoF[data$emoF == 18] <- 'disgust'
data$emoF[data$emoF == 19] <- 'dismissive'
data$emoF[data$emoF == 20] <- 'embarrassed'
```

```

data$emoF[data$emoF == 21] <- 'excited'
data$emoF[data$emoF == 22] <- 'focused'
data$emoF[data$emoF == 23] <- 'frustrated'
data$emoF[data$emoF == 24] <- 'grateful'
data$emoF[data$emoF == 25] <- 'guilty'
data$emoF[data$emoF == 26] <- 'happy'
data$emoF[data$emoF == 27] <- 'inspired'
data$emoF[data$emoF == 28] <- 'interested'
data$emoF[data$emoF == 29] <- 'jealous'
data$emoF[data$emoF == 30] <- 'lonely'
data$emoF[data$emoF == 31] <- 'loving'
data$emoF[data$emoF == 32] <- 'sad'
data$emoF[data$emoF == 33] <- 'superior'
data$emoF[data$emoF == 34] <- 'surprised'
data$emoF[data$emoF == 35] <- 'sympathetic'
data$emoF[data$emoF == 36] <- 'tired'
data$emoF <- as.factor(data$emoF)

##

# Number of People Interacting

data$socF <- data$numsoc
data$socF[data$socF == 1] <- "NA"
data$socF[data$socF == 2] <- "alone"
data$socF[data$socF == 3] <- "1"
data$socF[data$socF == 4] <- "2"
data$socF[data$socF == 5] <- "3-4"
data$socF[data$socF == 6] <- "5-10"
data$socF[data$socF == 7] <- "11-20"
data$socF[data$socF == 8] <- "20+"
data$socF <- as.factor(as.character(data$socF))

data$socF <- factor(data$socF, levels(data$socF)[c(7,1,3,5,6,2,4)])

#####
## Descriptive Statistics: Ratings ##
#####

# Objective features of the situation
summary(data$doF)
length(levels(data$doF)) # 26 situations
plot(data$doF)

round(summary(data$socF)/nrow(data[na.omit(data$socF),]), 2)

# Social hierarchy
hier.df <- with(data, data.frame(pow, stat, clas))
summary(hier.df)
sapply(hier.df, FUN = sd, na.rm = T)

#####
## DATA CLEAN: Calculating Multilevel Effects ##
#####

# CALCULATE between-person effects.
data <- within(data, pow.X <- ave(pow, idx, FUN = function(x) mean(x, na.rm = T)))
data <- within(data, stat.X <- ave(stat, idx, FUN = function(x) mean(x, na.rm = T)))

```

```

data <- within(data, clas.X <- ave(clas, idx, FUN = function(x) mean(x, na.rm = T)))

# CALCULATE within-person effects.
data <- within(data, pow.C <- (pow - pow.X))
data <- within(data, stat.C <- (stat - stat.X))
data <- within(data, clas.C <- (clas - clas.X))

# CALCULATE Lagged Effects
data$idx <- as.factor(data$idx)

data <- data[with(data, order(idx, code.time)),] # sort

data$pow.CL <- matrix(data = NA, nrow = nrow(data), ncol = 1)
data$stat.CL <- matrix(data = NA, nrow = nrow(data), ncol = 1)
data$clas.CL <- matrix(data = NA, nrow = nrow(data), ncol = 1)

data$pow.L <- matrix(data = NA, nrow = nrow(data), ncol = 1)
data$stat.L <- matrix(data = NA, nrow = nrow(data), ncol = 1)
data$clas.L <- matrix(data = NA, nrow = nrow(data), ncol = 1)

for (i in 1:length(levels(data$idx))) {
  data[data$idx == i,]$pow.CL <- with(data[data$idx == i,], c(rep(NA, 1), pow.C)[1 : length(pow.C)])
}
for (i in 1:length(levels(data$idx))) {
  data[data$idx == i,]$stat.CL <- with(data[data$idx == i,], c(rep(NA, 1), stat.C)[1 : length(stat.C)])
}
for (i in 1:length(levels(data$idx))) {
  data[data$idx == i,]$clas.CL <- with(data[data$idx == i,], c(rep(NA, 1), clas.C)[1 : length(clas.C)])
}

for (i in 1:length(levels(data$idx))) {
  data[data$idx == i,]$pow.L <- with(data[data$idx == i,], c(rep(NA, 1), pow)[1 : length(pow)])
}
for (i in 1:length(levels(data$idx))) {
  data[data$idx == i,]$stat.L <- with(data[data$idx == i,], c(rep(NA, 1), stat)[1 : length(stat)])
}
for (i in 1:length(levels(data$idx))) {
  data[data$idx == i,]$clas.L <- with(data[data$idx == i,], c(rep(NA, 1), clas)[1 : length(clas)])
}

## Figure 1: Distributions of Social Hierarchy.
fig1th <- theme_tufte(base_size = 14, base_family = 'HersheySans')

fig1P <- ggplot(data, aes(x = pow)) + xlab('Social Power') + ylim(0,1200) + geom_histogram(binwidth = .5) +
fig1th
fig1S <- ggplot(data, aes(x = stat)) + xlab('Social Status') + ylim(0,1200) + geom_histogram(binwidth = .5) +
fig1th
fig1C <- ggplot(data, aes(x = clas)) + xlab('Social Class') + ylim(0,1200) + geom_histogram(binwidth = .5) +
fig1th
x11()
grid.arrange(fig1P, fig1S, fig1C, ncol = 3)

#####
## Q1: How much do people vary in their social capital across different contexts? ##

```

```
#####
```

```
# Sample 1
pow.M1 <- lmer(pow ~ (1 | idx), data = s1, REML = F)
stat.M1 <- lmer(stat ~ (1 | idx), data = s1, REML = F)
clas.M1 <- lmer(clas ~ (1 | idx), data = s1, REML = F)

# Sample 2
pow.M1 <- lmer(pow ~ (1 | idx), data = s2, REML = F)
stat.M1 <- lmer(stat ~ (1 | idx), data = s2, REML = F)
clas.M1 <- lmer(clas ~ (1 | idx), data = s2, REML = F)

# ALL
pow.M1 <- lmer(pow ~ (1 | idx), data = data, REML = F)
stat.M1 <- lmer(stat ~ (1 | idx), data = data, REML = F)
clas.M1 <- lmer(clas ~ (1 | idx), data = data, REML = F)

pow.M1boot <- confint.merMod(pow.M1, method = 'boot', nsim = 999)
stat.M1boot <- confint.merMod(stat.M1, method = 'boot', nsim = 999)
clas.M1boot <- confint.merMod(clas.M1, method = 'boot', nsim = 999)

# Extract variance explained
pow.mod1s <- summary(pow.M1)
stat.mod1s <- summary(stat.M1)
clas.mod1s <- summary(clas.M1)

pow.ranFX1 <- VarCorr(pow.M1)
stat.ranFX1 <- VarCorr(stat.M1)
clas.ranFX1 <- VarCorr(clas.M1)

pow.fx <- pow.ranFX1$idx[1] / (pow.mod1s$sigma^2 + pow.ranFX1$idx[1])
pow.ci <- pow.M1boot[1,]^2/(pow.M1boot[1,]^2 + pow.M1boot[2,]^2)
pow.between <- (cbind(pow.fx, t(pow.ci)))

stat.fx <- stat.ranFX1$idx[1] / (stat.mod1s$sigma^2 + stat.ranFX1$idx[1])
stat.ci <- stat.M1boot[1,]^2/(stat.M1boot[1,]^2 + stat.M1boot[2,]^2)
stat.between <- (cbind(stat.fx, t(stat.ci)))

clas.fx <- clas.ranFX1$idx[1] / (clas.mod1s$sigma^2 + clas.ranFX1$idx[1])
clas.ci <- clas.M1boot[1,]^2/(clas.M1boot[1,]^2 + clas.M1boot[2,]^2)
clas.between <- (cbind(clas.fx, t(clas.ci)))

capital.bw.t <- rbind(pow.between, stat.between, clas.between)
row.names(capital.bw.t) <- c('power', 'status', 'class')
colnames(capital.bw.t) <- c('estimate', '2.5%', '97.5%')

round(capital.bw.t, 2)*100 # TABLE 1.
100 - round(capital.bw.t, 2)*100 #

# FIGURE 0: CALL-OUT OF THE STUFF.

dataex0 <- data[data$idx == 2,] # create subset of ppts for graphing.
dataex1 <- data[data$idx == c(2,3),] # create subset of ppts for graphing.
dataex2 <- data[data$idx == 3,]

## GRAPH COUNT, NOT DENSITY!

x11()
```

```

par(mfrow = c(2,1))
fig0ex0a <- with(dataex0, plot(code.time, pow, type = 'b', pch = 19,
                             xlab = "time", ylab = 'power', main = 'Participant #2'))
fig0ex0b <- with(dataex2, plot(code.time, pow, type = 'b', pch = 19,
                             xlab = "time", ylab = 'power', main = 'Participant #3'))

fig0ex0 <- ggplot(dataex0, aes(pow, fill = as.factor(idx))) + geom_freqpoly(alpha = .1) +
  ylab("Density\n") + xlab("\nSocial Power (Within-Person)") + xlim(1,5) +
  theme_tufte(base_size = 14, base_family = 'HersheySans') +
  theme(panel.margin = unit(5, "lines")) + guides(fill = F)

fig0ex1 <- ggplot(dataex1, aes(pow, fill = as.factor(idx))) + geom_density(alpha = .1) +
  ylab("Density\n") + xlab("\nSocial Power (Within-Person)") + ylim(0,1.5) + xlim(1,5) +
  theme_tufte(base_size = 14, base_family = 'HersheySans') +
  theme(panel.margin = unit(5, "lines")) + guides(fill = F)
fig0ex0
fig0ex1
x11()
fig0ex1 + geom_vline(xintercept = 4) + geom_vline(xintercept = 2.5)

# FIGURE 1: SUMMARY OF WITHIN-PERSON VARIATION: VISUALIZED.

dimension <- c("Power", "Status", "Class")
between <- c(pow.fx, stat.fx, clas.fx)
within <- 1 - c(pow.fx, stat.fx, clas.fx)

effect <- data.frame(t(rbind(between, within)), dimension)
effect2 <- melt(effect, id.var = 'dimension', variable_name = 'Variance')

levels(effect2[,2]) <- c("Between-Person", "Within-Person")
conf <- rbind(pow.ci, stat.ci, clas.ci)

fig1t <- data.frame(effect2)
fig1t$dimension <- factor(fig1t$dimension, levels(fig1t$dimension)[c(2,3,1)])

cols <- c('Between-Person'="darkgrey", 'Within-Person'="lightgrey")
fig1g <- ggplot(fig1t, aes(x = dimension, y = 100*value, fill = Variance)) +
  geom_bar(position = position_stack(), stat = 'identity') + xlab("Dimension of Social Hierarchy") +
  ylab("Percentage of Explained Variance") + ylim(c(0,100)) +
  geom_errorbar(data = fig1t[1:3,], aes(ymax = conf[,2]*100, ymin = conf[,1]*100),
               width=0.15, size = 2, colour = 'black') +
  theme_tufte(base_size = 14, base_family = 'HersheySans') + theme(legend.position='top')+
  scale_fill_manual(values = cols)
x11()
fig1g

# FIGURE 2: ACTUAL WITHIN-PERSON VARIATION: VISUALIZED!

x11()
names(data)
length(levels(as.factor(data[data$completed >20,]$idx))) # 24 ppts in Sample 1 completed > 75% of surveys
datag <- data[data$completed > 20,] # create subset of ppts for graphing.
#datag <- datag[!(datag$idx=="13"),] # remove
length(levels(as.factor(datag$idx)))

fig1pW <- ggplot(data, aes(pow.C, fill = as.factor(idx))) + geom_density(alpha = .0) +
  ylab("Density\n") + xlab("\nSocial Power (Within-Person)") + ylim(0,4) + xlim(-4,4) +

```

```

theme_tufte(base_size = 14, base_family = 'HersheySans') +
theme(panel.margin = unit(3, "lines")) + guides(fill = F)

fig1sW <- ggplot(data, aes(stat.C, fill = as.factor(idx))) + geom_density(alpha = .0) +
ylab("Density\n") + xlab("\nSocial Status (Within-Person)") +ylim(0,4) + xlim(-4,4) +
theme_tufte(base_size = 14, base_family = 'HersheySans') +
theme(panel.margin = unit(3, "lines")) + guides(fill = F)

fig1cW <- ggplot(data, aes(clas.C, fill = as.factor(idx))) + geom_density(alpha = .0) +
ylab("Density\n") + xlab("\nSocial Class (Within-Person)") + ylim(0,4) +xlim(-4,4) +
theme_tufte(base_size = 14, base_family = 'HersheySans') +
theme(panel.margin = unit(3, "lines")) + guides(fill = F)

grid.arrange(fig1g, fig1pW, fig1sW, fig1cW, ncol = 2)
#dev.off()

#####
## Q2: Do these factors differ in terms of their situational predictors? ##
#####

summary(pow.stat <- lmer(scale(stat) ~ scale(pow.C) + scale(pow.X) + (1 | idx), data = data))
summary(pow.clas <- lmer(scale(clas) ~ scale(pow.C) + scale(pow.X) + (1 | idx), data = data))
summary(stat.clas <- lmer(scale(clas) ~ scale(stat.C) + scale(stat.X) + (1 | idx), data = data))

summary(pow.stat <- lmer(stat ~ pow.C + pow.X + (1 | idx), data = data))
summary(pow.clas <- lmer(clas ~ pow.C + pow.X + (1 | idx), data = data))
summary(stat.clas <- lmer(clas ~ stat.C + stat.X + (1 | idx), data = data))

#pow.clasBoot <- confint.merMod(pow.clas, method = 'boot', nsim = 999)

## FIGURE 3: RELATION BETWEEN STATUS, POWER, CLASS AT DIFFERENT LEVELS: VISUALIZED!
x11() ### NEED 2 FIX ONE OF THE REGRESSION LINES!!
par(mfrow = c(3,2))
plot(data$pow.X, data$stat.X, xlab = "Power (Between-Person)", ylab = "Status (Between-Person)", pch = 19, cex
= .8,
main = "", xlim = c(1,5), ylim = c(1,5))
abline(a = fixef(pow.stat)[1], b = fixef(pow.stat)[3], lty = 1, col = 'red', lwd = 8)

plot(data$pow.C, data$stat.C, xlab = "Power (Within-Person)", ylab = "Status (Within-Person)", pch = 19, cex
= .8,
main = "", xlim = c(-4,4), ylim = c(-4,4))
abline(a = fixef(pow.stat)[1], b = fixef(pow.stat)[2], lty = 1, col = 'red', lwd = 8)

plot(data$pow.X, data$clas.X, xlab = "Power (Between-Person)", ylab = "Class (Between-Person)",
main = "", pch = 19, cex = .8, xlim = c(1,5), ylim = c(1,5))
abline(a = fixef(pow.clas)[1], b = fixef(pow.clas)[3], lty = 1, col = 'red', lwd = 8)

plot(data$pow.C, data$clas.C, xlab = "Power (Within-Person)", ylab = "Class (Within-Person)",
pch = 19, cex = .8, xlim = c(-4,4), ylim = c(-4,4))
abline(a = fixef(pow.clas)[1], b = fixef(pow.clas)[2], lty = 1, col = 'red', lwd = 8)

plot(data$stat.X, data$clas.X, xlab = "Status (Between-Person)", ylab = "Class (Between-Person)",
main = "", pch = 19, cex = .8, xlim = c(1,5), ylim = c(1,5))
abline(a = fixef(stat.clas)[1], b = fixef(stat.clas)[3], lty = 1, col = 'red', lwd = 8)

plot(data$stat.C, data$clas.C, xlab = "Status (Within-Person)", ylab = "Class (Within-Person)",
pch = 19, cex = .8, xlim = c(-4,4), ylim = c(-4,4))
abline(a = fixef(stat.clas)[1], b = fixef(stat.clas)[2], lty = 1, col = 'red', lwd = 8)

```

```

## Calculating Residual Variables for Power, Status, and Class
pow.resid <- lmer(scale(pow) ~ scale(clas) + scale(stat) + (1 | idx), data = data, REML = F,
na.action=na.exclude)
stat.resid <- lmer(scale(stat) ~ scale(clas) + scale(pow) + (1 | idx), data = data, REML = F,
na.action=na.exclude)
clas.resid <- lmer(scale(clas) ~ scale(stat) + scale(pow) + (1 | idx), data = data, REML = F,
na.action=na.exclude)

pow.resid # plenty of variance left to be explained!
.21^2 + .65^2 + .28^2 + .45^2

stat.resid
clas.resid

vif.mer(pow.resid) # Making sure there's not too much autocorrelation.
vif.mer(stat.resid)
vif.mer(clas.resid)

pow.R <- residuals(pow.resid)
stat.R <- residuals(stat.resid)
clas.R <- residuals(clas.resid)

x11()
par(mfrow = c(1,3))
hist(pow.R, col = 'black', bor = 'white', main = "", xlab = "Social Power (Residual)")
hist(stat.R, col = 'black', bor = 'white', main = "", xlab = "Social Status (Residual)")
hist(clas.R, col = 'black', bor = 'white', main = "", xlab = "Social Class (Residual)")

#####
# POWER, STATUS, CLASS DIFFER AS A FUNCTION OF FEATURES OF THE SITUATION ##
#####

# What the Person Was Doing and Who the Person was With
## modeling
summary(pow.sitFX <- lmer(pow.R ~ -1 + doF + (1 | idx), data = data, REML = F))
summary(stat.sitFX <- lmer(stat.R ~ -1 + doF + (1 | idx), data = data, REML = F))
summary(clas.sitFX <- lmer(clas.R ~ -1 + doF + (1 | idx), data = data, REML = F))

summary(pow.socFX <- lmer(pow.R ~ -1 + socF + (1 | idx), data = data, REML = F))
summary(stat.socFX <- lmer(stat.R ~ -1 + socF + (1 | idx), data = data, REML = F))
summary(clas.socFX <- lmer(clas.R ~ -1 + socF + (1 | idx), data = data, REML = F))

## do features of the situation explain variance?
Anova(pow.sitFX) # definitely power !
Anova(stat.sitFX) # and status
Anova(clas.sitFX) # to a lesser (but still significant extent; class)
anova(clas.sitFX, pow.sitFX)

Anova(stat.socFX) # definitely!
Anova(pow.socFX) # yeah
Anova(clas.socFX) # not really!

## ALSO MEASURED WHO PARTICIPANTS WERE WITH IN S1, BUT:.
summary(s1$relF) # not enough participants rated who they were with.

## FIGURE 4: SITUATIONAL PREDICTORS OF SOCIAL CAPITAL: VISUALIZED
## Graphing

```



```

pow.sitFXX <- fixef(pow.sitFX) # extract fixed effects estimates
stat.sitFXX <- fixef(stat.sitFX)
clas.sitFXX <- fixef(clas.sitFX)

pow.sitSE <- sqrt(diag(vcov(pow.sitFX))) # extract fixed effects standard errors
stat.sitSE <- sqrt(diag(vcov(stat.sitFX)))
clas.sitSE <- sqrt(diag(vcov(clas.sitFX)))

# calculate error bars
pow.sit.lim <- aes(ymax = pow.sitFXX + pow.sitSE, ymin= pow.sitFXX - pow.sitSE)
stat.sit.lim <- aes(ymax = stat.sitFXX + stat.sitSE, ymin= stat.sitFXX - stat.sitSE)
clas.sit.lim <- aes(ymax = clas.sitFXX + clas.sitSE, ymin= clas.sitFXX - clas.sitSE)

hier.sit.lim <- aes(ymax = c(pow.sitFXX + pow.sitSE,
                             stat.sitFXX + stat.sitSE,
                             clas.sitFXX + clas.sitSE),
                  ymin = c(pow.sitFXX - pow.sitSE,
                             stat.sitFXX - stat.sitSE,
                             clas.sitFXX - clas.sitSE))

hier.sit <- melt(cbind(Power = pow.sitFXX, Status = stat.sitFXX, Class = clas.sitFXX))
colnames(hier.sit) <- c('sit', 'Dimension', 'effect')
situations <- factor(levels(data$doF), levels = levels(data$doF)) # creates labels for axis.
levels(hier.sit$sit) <- levels(situations)

## ALL SITUATIONS
cols <- c(Power = '#636363', Status = '#bdbdbd', Class = '#f0f0f0')
x11()
hier.sit.G <- ggplot(hier.sit, aes(x = sit, y = effect, fill = dimension)) +
  geom_bar(position = position_dodge(.9), stat = 'identity') + coord_flip() +
  geom_errorbar(hier.sit.lim, position = position_dodge(.9),
               width = .5, size = .3, colour = 'black') +
  xlab('\nSituation (What the Person Was Doing)\n') + ylab("Unique Effect") +
  theme_tufte(base_size = 14, base_family = 'HersheySans') +
  scale_fill_manual(values = cols)
  #scale_fill_brewer(palette="OrRd")
hier.sit.G

## SUBSETTED SITUATIONS

data[data$Code %in% selected,]
sitSUB <- levels(hier.sit$sit)[c(6, 7, 13, 16, 19, 26)]
hier.sit$sitSUB <- levels(hier.sit$sit)[c(6, 7, 13, 16, 19, 26)]
hier.sitSUB <- hier.sit[hier.sit$sit %in% sitSUB,]

hier.sit.limSUB <- aes(ymax = c(pow.sitFXX[c(6, 7, 13, 16, 19, 26)] + pow.sitSE[c(6, 7, 13, 16, 19, 26)],
                               stat.sitFXX[c(6, 7, 13, 16, 19, 26)] + stat.sitSE[c(6, 7, 13, 16, 19, 26)],
                               clas.sitFXX[c(6, 7, 13, 16, 19, 26)] + clas.sitSE[c(6, 7, 13, 16, 19, 26)]),
                    ymin = c(pow.sitFXX[c(6, 7, 13, 16, 19, 26)] - pow.sitSE[c(6, 7, 13, 16, 19, 26)],
                               stat.sitFXX[c(6, 7, 13, 16, 19, 26)] - stat.sitSE[c(6, 7, 13, 16, 19, 26)],
                               clas.sitFXX[c(6, 7, 13, 16, 19, 26)] - clas.sitSE[c(6, 7, 13, 16, 19, 26)]))

x11()
hier.sit.G <- ggplot(hier.sitSUB, aes(x = sit, y = effect, fill = Dimension)) +
  geom_bar(position = position_dodge(.9), stat = 'identity') + coord_flip() +
  geom_errorbar(hier.sit.limSUB, position = position_dodge(.9),
               width = .5, size = .3, colour = 'black') +

```

```

xlab('\nSituation (What the Person Was Doing)\n') + ylab("Unique Effect") +
theme_tufte(base_size = 14, base_family = 'HersheySans') +
scale_fill_manual(values = cols)
#scale_fill_brewer(palette="OrRd")
hier.sit.G

## THIS GRAPH, SEPARATELY
pow.sit.G <- qplot(situations, pow.sitFXX, geom = 'bar', stat = 'identity') +
  ylab('\nSituational Power\n') + coord_flip() +
  xlab('\nSituation (What the Person Was Doing)\n') +
  geom_errorbar(pow.sit.lim, width=0.5, colour = 'gray') +
  theme_tufte(base_size = 11, base_family = 'HersheySans')

stat.sit.G <- qplot(situations, stat.sitFXX, geom = 'bar', stat = 'identity') +
  ylab('\nSituational Status\n') + coord_flip() +
  xlab('\nSituation (What the Person Was Doing)\n') +
  geom_errorbar(stat.sit.lim, width=0.5, colour = 'gray') +
  theme_tufte(base_size = 11, base_family = 'HersheySans')

clas.sit.G <- qplot(situations, clas.sitFXX, geom = 'bar', stat = 'identity') +
  ylab('\nSituational Class\n') + coord_flip() +
  xlab('\nSituation (What the Person Was Doing)\n') +
  geom_errorbar(clas.sit.lim, width=0.5, colour = 'gray') +
  theme_tufte(base_size = 11, base_family = 'HersheySans')

## FIGURE 5: Graphing: Who the Person was With
pow.socFXX <- fixef(pow.socFX) # extract fixed effects estimates
stat.socFXX <- fixef(stat.socFX)
clas.socFXX <- fixef(clas.socFX)

pow.socSE <- sqrt(diag(vcov(pow.socFX))) # extract fixed effects standard errors
stat.socSE <- sqrt(diag(vcov(stat.socFX)))
clas.socSE <- sqrt(diag(vcov(clas.socFX)))

# calculate error bars
pow.soc.lim <- aes(ymax = pow.socFXX + pow.socSE, ymin= pow.socFXX - pow.socSE)
stat.soc.lim <- aes(ymax = stat.socFXX + stat.socSE, ymin= stat.socFXX - stat.socSE)
clas.soc.lim <- aes(ymax = clas.socFXX + clas.socSE, ymin= clas.socFXX - clas.socSE)

hier.soc.lim <- aes(ymax = c(pow.socFXX + pow.socSE,
                           stat.socFXX + stat.socSE,
                           clas.socFXX + clas.socSE),
                  ymin = c(pow.socFXX - pow.socSE,
                           stat.socFXX - stat.socSE,
                           clas.socFXX - clas.socSE))

hier.soc <- melt(cbind(Power = pow.socFXX, Status = stat.socFXX, Class = clas.socFXX))
colnames(hier.soc) <- c('soc', 'Dimension', 'effect')

social <- factor(levels(data$socF), levels = levels(data$socF)) # creates labels for axis.
levels(hier.soc$soc) <- rev(levels(social))

cols <- c(Power = '#636363', Status = '#bdbdbd', Class = '#f0f0f0')
#x11()
hier.soc.G <- ggplot(hier.soc, aes(x = soc, y = effect, fill = Dimension)) +
  geom_bar(position = position_dodge(.9), stat = 'identity') + coord_flip() +
  geom_errorbar(hier.soc.lim, position = position_dodge(.9),
               width = .5, size = .3, colour = 'black') +
  xlab('\nSituation (Number of Others the Person Was With)\n') + ylab("Unique Effect") +

```

```

theme_tufte(base_size = 14, base_family = 'HersheySans') +
geom_hline(aes(xintercept = 0)) +
scale_fill_manual(values = cols)
hier.soc.G

pow.soc.G <- qplot(social, pow.socFXX, geom = 'bar', stat = 'identity') +
  ylab('\nSituational Power\n') + coord_flip() +
  xlab('\nSituation (# of Other People in Interaction)\n') +
  geom_errorbar(pow.soc.lim, width=0.5, colour = 'gray') +
  theme_tufte(base_size = 11, base_family = 'HersheySans')

stat.soc.G <- qplot(social, stat.socFXX, geom = 'bar', stat = 'identity') +
  ylab('\nSituational Status\n') + coord_flip() +
  xlab('\nSituation (# of Other People in Interaction)\n') +
  geom_errorbar(stat.soc.lim, width=0.5, colour = 'gray') +
  theme_tufte(base_size = 11, base_family = 'HersheySans')

clas.soc.G <- qplot(social, clas.socFXX, geom = 'bar', stat = 'identity') +
  ylab('\nSituational Class\n') + coord_flip() +
  xlab('\nSituation (# of Other People in Interaction)\n') +
  geom_errorbar(clas.soc.lim, width=0.5, colour = 'gray') +
  theme_tufte(base_size = 11, base_family = 'HersheySans')

x11()
grid.arrange(stat.sit.G, pow.sit.G, clas.sit.G, ncol = 3)

grid.arrange(stat.soc.G, pow.soc.G, clas.soc.G, ncol = 3)

#####
## Q3: Do these factors differ in terms of their outcomes? ##
#####
## Class predicts changes in power.

summary(mod1 <- lmer(scale(pow.L) ~ scale(clas) + scale(pow) + scale(stat) + scale(code.time) + (1 | idx), data
= data, REML = F))
summary(mod2 <- lmer(scale(stat.L) ~ scale(clas) + scale(pow) + scale(stat) + scale(code.time) + (1 | idx),
data = data, REML = F))
summary(mod3 <- lmer(scale(clas.L) ~ scale(clas) + scale(pow) + scale(stat) + scale(code.time) + (1 | idx),
data = data, REML = F))

mod1boot <- confint.merMod(mod1, method = 'boot', nsim = 999)
mod2boot <- confint.merMod(mod2, method = 'boot', nsim = 999)
mod3boot <- confint.merMod(mod3, method = 'boot', nsim = 999)

mod1boot
mod2boot
mod3boot

```

R Code: Chapter Figures and Analyses - Chapter 3

```
#####  
## LOAD LIBRARIES                                     ###  
#####  
  
library(lme4)  
library(car)  
library(psych)  
library(ggplot2)  
library(ggthemes)  
library(grid)  
library(gridExtra)  
  
set.seed(12345) # ensures reproducibility of bootstrapped results.  
  
setwd('~Downloads/Dropbox/Research/Dissertation/Chapter: Suppression in Everyday Life/')  
  
#####  
## LOAD DATA: And some merging / de-identifying     ##  
#####  
  
# Sample 1  
s1 <- read.csv('data//esm_sample1_deID.csv')  
s1S <- read.csv('data//dem_sample1_deID.csv')  
  
names(s1)  
  
s1$idx  
names(s1S)  
  
# Sample 2  
s2 <- read.csv('data/esm_sample2_deID.csv')  
s2S <- read.csv('data//dem_sample2_deID.csv')  
  
names(s2)  
names(s2S)  
  
#####  
## Demographics                                     ###  
#####  
  
# sample size  
nrow(s1S)  
nrow(s2S)  
nrow(s2S) + nrow(s1S)  
  
# gender  
summary(s1S$sex)  
summary(s1S$sex) / nrow(s1S)  
  
summary(as.factor(s2S$sex)) # 1 = male; 2 = female  
summary(as.factor(s2S$sex)) / nrow(s2S)  
  
# ethnicity  
summary(s1S$eth) / nrow(s1S)
```

```

summary(s2S$ethF) / nrow(s2S)

#####
## DATA CLEAN: Calculate within and between-person FX ##
#####

# CALCULATE composite ratings for related constructs

alpha(with(s1, data.frame(s.pow, s.stat, s.clas)))
s1 <- within(s1, s.POW <- (s.pow + s.stat + s.clas)/3)

with(s2, cor.test(pow, stat))
s2 <- within(s2, pwst <- (pow + stat)/2)

with(s1, cor.test(s.e, s.eR))
s1 <- within(s1, s.E <- (s.e + s.eR)/2) # reverse scored personality items.

## Well-Being
with(s1, cor.test(s.sise, eVal))
with(s2, cor.test(sise, feel))
s1 <- within(s1, s.WB <- (s.sise + eVal)/2)
s2 <- within(s2, s.WB <- ((sise + feel)/2))

# CALCULATE between-person effects.

# Emotion and Emotion Regulation Measures

s1 <- within(s1, s.sup.X <- ave(s.sup, idx, FUN = function(x) mean(x, na.rm = T)))
s1 <- within(s1, s.rea.X <- ave(s.rea, idx, FUN = function(x) mean(x, na.rm = T)))

s2 <- within(s2, sup.X <- ave(sup, idx, FUN = function(x) mean(x, na.rm = T)))

# Personality, Power, and Well-Being
s1 <- within(s1, s.pow.X <- ave(s.POW, idx, FUN = function(x) mean(x, na.rm = T)))
s1 <- within(s1, s.power.X <- ave(s.pow, idx, FUN = function(x) mean(x, na.rm = T)))
s1 <- within(s1, s.status.X <- ave(s.stat, idx, FUN = function(x) mean(x, na.rm = T)))

s2 <- within(s2, pwst.X <- ave(pwst, idx, FUN = function(x) mean(x, na.rm = T)))

s1 <- within(s1, s.e.X <- ave(s.E, idx, FUN = function(x) mean(x, na.rm = T)))
s2 <- within(s2, e.X <- ave(ext, idx, FUN = function(x) mean(x, na.rm = T)))

s1 <- within(s1, s.WB.X <- ave(s.WB, idx, FUN = function(x) mean(x, na.rm = T)))
s2 <- within(s2, s.WB.X <- ave(s.WB, idx, FUN = function(x) mean(x, na.rm = T)))

s1 <- within(s1, sise.X <- ave(s.sise, idx, FUN = function(x) mean(x, na.rm = T)))
s1 <- within(s1, feel.X <- ave(eVal, idx, FUN = function(x) mean(x, na.rm = T)))

s2 <- within(s2, sise.X <- ave(sise, idx, FUN = function(x) mean(x, na.rm = T)))
s2 <- within(s2, feel.X <- ave(feel, idx, FUN = function(x) mean(x, na.rm = T)))
s2 <- within(s2, auth.X <- ave(auth, idx, FUN = function(x) mean(x, na.rm = T)))
# CALCULATE within-person effects.

# Emotion and Emotion Regulation Measures
s1 <- within(s1, s.sup.C <- (s.sup - s.sup.X))

```

```

s1 <- within(s1, s.rea.C <- (s.rea - s.rea.X))

s2 <- within(s2, sup.C <- (sup - sup.X))

# Personality, Status, Self- and Other-Evaluation Measures

s1 <- within(s1, s.pow.C <- s.POW - s.pow.X)
s1 <- within(s1, s.e.C <- s.E - s.e.X)

s1 <- within(s1, s.WB.C <- s.WB - s.WB.X)
s1 <- within(s1, s.sise.C <- s.sise - sise.X)
s1 <- within(s1, feel.C <- eVal - feel.X)

s2 <- within(s2, pwst.C <- pwst - pwst.X)
s2 <- within(s2, e.C <- ext - e.X)

s2 <- within(s2, s.WB.C <- s.WB - s.WB.X)
s2 <- within(s2, sise.C <- sise - sise.X)
s2 <- within(s2, feel.C <- feel - feel.X)
s2 <- within(s2, auth.C <- auth - auth.X)

#####
## Q1: How Much Within-Person Variation?      ###
#####

summary(sup.s1 <- lmer(s.sup ~ 1 + (1 | idx), data = s1, REML = F))
sup.s1boot <- confint.merMod(sup.s1, method = 'boot', nsim = 999)
sup.s1boot

summary(sup.s2 <- lmer(sup ~ 1 + (1 | idx), data = s2, REML = F))
sup.s2boot <- confint.merMod(sup.s2, method = 'boot', nsim = 999)
sup.s2boot

summary(rea.s1 <- lmer(s.rea ~ 1 + (1 | idx), data = s1, REML = F))
rea.s1boot <- confint.merMod(rea.s1, method = 'boot', nsim = 999)
rea.s1boot

summary(ext.s1 <- lmer(s.E ~ 1 + (1 | idx), data = s1, REML = F))
ext.s1boot <- confint.merMod(ext.s1, method = 'boot', nsim = 999)
ext.s1boot

summary(ext.s2 <- lmer(ext ~ 1 + (1 | idx), data = s2, REML = F))
ext.s2boot <- confint.merMod(ext.s2, method = 'boot', nsim = 999)
ext.s2boot

summary(pow.s1 <- lmer(s.POW ~ 1 + (1 | idx), data = s1, REML = F))
pow.s1boot <- confint.merMod(pow.s1, method = 'boot', nsim = 999)
pow.s1boot

summary(pow.s2 <- lmer(pwst ~ 1 + (1 | idx), data = s2, REML = F))
pow.s2boot <- confint.merMod(pow.s2, method = 'boot', nsim = 999)
pow.s2boot

## Calculating the Percentage of Between-Person Variation

## Suppression
sup.s10 <- summary(sup.s1) # extract % variance explained by between-person differences in suppression
sup.s1.ran <- VarCorr(sup.s1)
s1.q0 <- sup.s1.ran$idx[1] / (sup.s10$sigma^2 + sup.s1.ran$idx[1])

```

```

s1.q1 <- sup.s1boot[1,]^2/(sup.s1boot[1,]^2 + sup.s1boot[2,]^2)

s1.wi <- sup.s10$sigma^2 / (sup.s10$sigma^2 + sup.s1.ran$idx[1])
s1.wiCI <- sup.s1boot[2,]^2 / (sup.s1boot[1,]^2 + sup.s1boot[2,]^2)

sup.s20 <- summary(sup.s2) # extract % variance explained by between-person differences in suppression
sup.s2.ran <- VarCorr(sup.s2)
s2.q0 <- sup.s2.ran$idx[1] / (sup.s20$sigma^2 + sup.s2.ran$idx[1])
s2.q1 <- sup.s2boot[1,]^2/(sup.s2boot[1,]^2 + sup.s2boot[2,]^2)

s2.wi <- sup.s20$sigma^2 / (sup.s20$sigma^2 + sup.s2.ran$idx[1])
s2.wiCI <- sup.s2boot[2,]^2 / (sup.s2boot[1,]^2 + sup.s2boot[2,]^2)

## Reappraisal
rea.s10 <- summary(rea.s1) # extract % variance explained by between-person differences in reappraisal
rea.s1.ran <- VarCorr(rea.s1)
r1.q0 <- rea.s1.ran$idx[1] / (rea.s10$sigma^2 + rea.s1.ran$idx[1])
r1.q1 <- rea.s1boot[1,]^2/(rea.s1boot[1,]^2 + rea.s1boot[2,]^2)

## Extraversion
ext.s10 <- summary(ext.s1) # extract % variance explained by between-person differences in extraversion
ext.s1.ran <- VarCorr(ext.s1)
e1.q0 <- ext.s1.ran$idx[1] / (ext.s10$sigma^2 + ext.s1.ran$idx[1])
e1.q1 <- ext.s1boot[1,]^2/(ext.s1boot[1,]^2 + ext.s1boot[2,]^2)

ext.s20 <- summary(ext.s2) # extract % variance explained by between-person differences in extraversion
ext.s2.ran <- VarCorr(ext.s2)
e2.q0 <- ext.s2.ran$idx[1] / (ext.s20$sigma^2 + ext.s2.ran$idx[1])
e2.q1 <- ext.s2boot[1,]^2/(ext.s2boot[1,]^2 + ext.s2boot[2,]^2)

## Power
pow.s10 <- summary(pow.s1) # powract % variance explained by between-person differences in powrversion
pow.s1.ran <- VarCorr(pow.s1)
p1.q0 <- pow.s1.ran$idx[1] / (pow.s10$sigma^2 + pow.s1.ran$idx[1])
p1.q1 <- pow.s1boot[1,]^2/(pow.s1boot[1,]^2 + pow.s1boot[2,]^2)

pow.s20 <- summary(pow.s2) # powract % variance explained by between-person differences in powrversion
pow.s2.ran <- VarCorr(pow.s2)
p2.q0 <- pow.s2.ran$idx[1] / (pow.s20$sigma^2 + pow.s2.ran$idx[1])
p2.q1 <- pow.s2boot[1,]^2/(pow.s2boot[1,]^2 + pow.s2boot[2,]^2)

q1.between.tab <- rbind('suppression' = c('estimate' = s1.q0, 'CI' = s1.q1),
                       'reappraisal' = c(r1.q0, r1.q1),
                       'extraversion' = c(e1.q0, e1.q1),
                       'power' = c(p1.q0, p1.q1))

q1.between.tab2 <- rbind('suppression' = c('estimate' = s2.q0, 'CI' = s2.q1),
                        'reappraisal' = c(NA, NA),
                        'extraversion' = c(e2.q0, e2.q1),
                        'power' = c(p2.q0, p2.q1))

between.fx.t1 <- round(q1.between.tab*100, 1)
between.fx.t2 <- round(q1.between.tab2*100, 1)

cbind(between.fx.t1, between.fx.t2) # Table 2: Between-Person Variance
cbind(100-between.fx.t1, 100-between.fx.t2) # Table 2: Within-Person Variance (flip 2.5 & 97.5% CI)

##### WITHIN-PERSON VARIANCE; VISUALIZED!! #####

```

```

length(levels(as.factor(s1[s1$completed > 30,]$idx))) # 41 ppts in Sample 1 completed > 75% of surveys
sig <- s1[s1$completed > 30,] # create subset of ppts for graphing.
sig <- sig[!(sig$idx=="13"),] # remove
length(levels(as.factor(sig$idx)))

fig1s <- ggplot(sig, aes(s.sup.C, fill = as.factor(idx))) + geom_density(alpha = .0) +
  ylab("Density\n") + xlab("\nSituational Suppression (Within-Person)") +
  theme_tufte(base_size = 11, base_family = 'Garamond') +
  theme(panel.margin = unit(3, "lines")) + guides(fill = F)

fig1r <- ggplot(sig, aes(s.rea.C, fill = as.factor(idx))) + geom_density(alpha = .0) +
  ylab("Density\n") + xlab("\nSituational Reappraisal (Within-Person)") +
  theme_tufte(base_size = 11, base_family = 'Garamond') +
  theme(panel.margin = unit(3, "lines")) + guides(fill = F)

x11()
grid.arrange(fig1s, fig1r)

#####
## Q2: When Do People Vary in Suppression?      ###
#####

# Some data-cleaning:
s2$doF <- as.factor(s2$doF) # situations are the same; but have different labels.
levels(s1$doF)[c(10, 13, 24)] <- c("music", "facebook", "tv")
levels(s1$doF) <- levels(as.factor(as.character(s1$doF)))

## Null Models:
summary(sup.sit.m0.1 <- lmer(scale(s.sup) ~ -1 + (1 | idx), data = s1, REML = F))
summary(sup.sit.m0.2 <- lmer(scale(sup) ~ (1 | idx), data = s2, REML = F))

## Features of the Situation: What the Person Was Doing
summary(sup.sit.m1.1 <- lmer(scale(s.sup) ~ doF -1 + (1 | idx), data = s1, REML = F))
summary(sup.sit.m1.2 <- lmer(scale(sup) ~ doF -1 + (1 | idx), data = s2, REML = F))

## Features of the Situation: Who the Person Was With
summary(sup.sit.m2.1 <- lmer(scale(s.sup) ~ socF -1 + (1 | idx), data = s1, REML = F))
summary(sup.sit.m2.2 <- lmer(scale(sup) ~ socF -1 + (1 | idx), data = s2, REML = F))

## Combined Model
summary(sup.sit.m3.1 <- lmer(scale(s.sup) ~ doF + socF -1 + (1 | idx), data = s1, REML = F))
summary(sup.sit.m3.2 <- lmer(scale(sup) ~ doF + socF -1 + (1 | idx), data = s2, REML = F))

## Compare models
Anova(sup.sit.m3.1)
Anova(sup.sit.m3.2)

## Variance Inflation Factor Function
## Function written by Austin Frank: https://github.com/auf frank/R-hacks/blob/master/mer-utils.R
vif.mer <- function (fit) {
  ## adapted from rms::vif

  v <- vcov(fit)
  nam <- names(fixef(fit))

  ## exclude intercepts
  ns <- sum(1 * (nam == "Intercept" | nam == "(Intercept)"))

```



```

if (ns > 0) {
  v <- v[-(1:ns), -(1:ns), drop = FALSE]
  nam <- nam[-(1:ns)]
}

d <- diag(v)^0.5
v <- diag(solve(v/(d %>% d)))
names(v) <- nam
v
}

vif.mer(sup.sit.m3.1)
vif.mer(sup.sit.m3.2)

## Graphs: Features of the situation

situations1 <- factor(levels(s1$doF), levels = levels(s1$doF)) # creates labels for axis.
situations2 <- factor(levels(as.factor(s2$doF)), levels = levels(as.factor(s2$doF))) # creates labels for axis.
cbind(levels(situations1), levels(situations2)) # making sure they are the same

social1 <- factor(levels(s1$socF), levels = levels(s1$socF))
social2 <- factor(levels(s2$socF), levels = levels(s2$socF))
cbind(levels(social1), levels(social2)) # not the same! need to re-level.

# s1$socF <- factor(s1$socF, levels(s1$socF)[c(7,1,3,5,6,2,4)]) # relevel factor.

sup.sitFX1 <- fixef(sup.sit.m1.1) # extract fixed effects estimates
sup.sitFX2 <- fixef(sup.sit.m1.2)

sup.socFX1 <- fixef(sup.sit.m2.1)
sup.socFX2 <- fixef(sup.sit.m2.2)

sup.sitSE1 <- sqrt(diag(vcov(sup.sit.m1.1))) # extract fixed effects standard errors
sup.sitSE2 <- sqrt(diag(vcov(sup.sit.m1.2)))

sup.socSE1 <- sqrt(diag(vcov(sup.sit.m2.1)))
sup.socSE2 <- sqrt(diag(vcov(sup.sit.m2.2)))

# calculate error bars
sup.sit.lim1 <- aes(ymax = sup.sitFX1 + sup.sitSE1, ymin= sup.sitFX1 - sup.sitSE1)
sup.sit.lim2 <- aes(ymax = sup.sitFX2 + sup.sitSE2, ymin= sup.sitFX2 - sup.sitSE2)

sup.soc.lim1 <- aes(ymax = sup.socFX1 + sup.socSE1, ymin= sup.socFX1 - sup.socSE1)
sup.soc.lim2 <- aes(ymax = sup.socFX2 + sup.socSE2, ymin= sup.socFX2 - sup.socSE2)

sit.sup.G1 <- qplot(situations1, sup.sitFX1, geom = 'bar', stat = 'identity',) +
  ylab('Situational Suppression Use\n\nSample 1') + coord_flip() +
  xlab('\nSituation (What the Person Was Doing)') +
  geom_errorbar(sup.sit.lim1, width=0.5, colour = 'gray') +
  theme_tufte(base_size = 11, base_family = 'Garamond')

sit.sup.G2 <- qplot(situations2, sup.sitFX2, geom = 'bar', stat = 'identity',) +
  ylab('\nSituational Suppression Use\n\nSample 2') + coord_flip() +
  xlab('\nSituation (What the Person Was Doing)') +
  geom_errorbar(sup.sit.lim2, width=0.5, colour = 'gray') +
  theme_tufte(base_size = 11, base_family = 'Garamond')

soc.sup.G1 <- qplot(social1, sup.socFX1, geom = 'bar', stat = 'identity',) +
  ylab('Situational Suppression Use\n\nSample 1') + coord_flip() +

```

```

xlab('\nSocial Interaction (Who the Person Was With)') +
geom_errorbar(sup.soc.lim1, width=0.5, colour = 'gray') +
theme_tufte(base_size = 11, base_family = 'Garamond')

soc.sup.G2 <- qplot(social2, sup.socFX2, geom = 'bar', stat = 'identity',) +
  ylab('Situational Suppression Use\n\nSample 2') + coord_flip() +
  xlab('\nSocial Interaction (Who the Person Was With)') +
  geom_errorbar(sup.soc.lim2, width=0.5, colour = 'gray') +
  theme_tufte(base_size = 11, base_family = 'Garamond')

x11()
grid.arrange(sit.sup.G1, sit.sup.G2, ncol = 2)
grid.arrange(soc.sup.G1, soc.sup.G2, ncol = 2)

## Trying to merge together for single graph...failed to make this look good.
#sup.sitFXall <- rbind(data.frame(FX = sup.sitFX1, sample = "s1", situation = situations1),
#                      data.frame(FX = sup.sitFX2, sample = "s2", situation = situations2))
#sup.sitSEall <- rbind(data.frame(SE = sup.sitSE1, sample = "s1"),
#                      data.frame(SE = sup.sitSE2, sample = "s2"))

#sup.sitLIM <- rbind(data.frame(LIM = sup.sit.lim1, sample = "s1"),
#                   data.frame(LIM = sup.sit.lim2, sample = "s2"))

#sup.sitSEall <- cbind(Sample1 = sup.sitSE1, Sample2 = sup.sitSE2)
#sup.sitLIM <- cbind(Sample1 = sup.sit.lim1, Sample2 = sup.sit.lim2)

#sit.supG <- ggplot(sup.sitFXall) +
#  geom_bar(aes(y = FX, x = situation, fill = sample), stat = "identity",
#           position = "dodge", width = .5) + coord_flip() +
#  theme_tufte(base_size = 11, base_family = 'Garamond') +
#  geom_errorbar(sup.sitLIM, width = .5, color = 'gray')

## Features of the Person: Extraversion and Social Capital

## Descriptive Statistics of the Predictor Variables
pers.df1 <- with(s1, data.frame(s.e.X, s.e.C, s.pow.X, s.pow.C))
pers.df2 <- with(s2, data.frame(e.X, e.C, pwst.X, pwst.C))

summary(pers.df1)
summary(pers.df2)
corr.test(pers.df1)
corr.test(pers.df2)

## Null Model:
summary(sup.pers.m0.1 <- lmer(scale(s.sup) ~ scale(time.days) + scale(time.hour) +
                             (1 | idx), data = s1, REML = F))

summary(sup.pers.m0.2 <- lmer(scale(sup) ~ scale(day) + scale(hr) +
                             (1 | idx), data = s2, REML = F))

## Extraversion
summary(sup.pers.m1.1 <- lmer(scale(s.sup) ~ scale(s.e.X) + scale(s.e.C) +
                             scale(time.days) + scale(time.hour) +
                             (1 | idx), data = s1, REML = F))

summary(sup.pers.m1.2 <- lmer(scale(sup) ~ scale(e.X) + scale(e.C) +

```

```

        scale(day) + scale(hr) +
        (1 | idx), data = s2, REML = F))

## Social Capital:
summary(sup.pers.m2.1 <- lmer(scale(s.sup) ~ scale(s.pow.X) + scale(s.pow.C) +
        scale(time.days) + scale(time.hour) +
        (1 | idx), data = s1, REML = F))

summary(sup.pers.m2.2 <- lmer(scale(sup) ~ scale(pwst.X) + scale(pwst.C) +
        scale(day) + scale(hr) +.34
        (1 | idx), data = s2, REML = F))

## Full Model:
summary(sup.pers.m3.1 <- lmer(scale(s.sup) ~ scale(s.e.X) + scale(s.e.C) +
        scale(s.pow.X) + scale(s.pow.C) +
        scale(time.days) + scale(time.hour) +
        (1 | idx), data = s1, REML = F))

summary(sup.pers.m3.2 <- lmer(scale(sup) ~ scale(e.X) + scale(e.C) +
        scale(pwst.X) + scale(pwst.C) +
        scale(day) + scale(hr) +
        (1 | idx), data = s2, REML = F))

summary(sup.pers.m3.1 <- lmer(scale(s.sup) ~ scale(s.e.X) + scale(s.e.C) +
        scale(s.pow.X) + scale(s.pow.C) + scale(s.fne)+
        scale(time.days) + scale(time.hour) +
        (1 | idx), data = s1, REML = F))

summary(sup.pers.m3.2 <- lmer(scale(sup) ~ scale(e.X) + scale(e.C) +
        scale(pwst.X) + scale(pwst.C) +
        scale(day) + scale(hr) +
        (1 | idx), data = s2, REML = F))

## Bootstrapping CIs

sup.pers.boot11 <- confint.merMod(sup.pers.m1.1, method = 'boot', nsim = 999)
sup.pers.boot12 <- confint.merMod(sup.pers.m1.2, method = 'boot', nsim = 999)

sup.pers.boot21 <- confint.merMod(sup.pers.m2.1, method = 'boot', nsim = 999)
sup.pers.boot22 <- confint.merMod(sup.pers.m2.2, method = 'boot', nsim = 999)

sup.pers.boot31 <- confint.merMod(sup.pers.m3.1, method = 'boot', nsim = 999)
sup.pers.boot32 <- confint.merMod(sup.pers.m3.2, method = 'boot', nsim = 999)

sup.pers.boot11
sup.pers.boot12
sup.pers.boot21
sup.pers.boot22
sup.pers.boot31
sup.pers.boot32

## Model Diagnostics

anova(sup.pers.m3.1, sup.pers.m0.1)
anova(sup.pers.m3.2, sup.pers.m0.2)

vif.mer(sup.pers.m3.1)
vif.mer(sup.pers.m3.2)

Anova(sup.pers.m3.1)

```

```

Anova(sup.pers.m3.2)

sup.pers.boot3.1 <- confint.merMod(sup.pers.m3.1, method = 'b', nsim = 999)
sup.pers.boot3.2 <- confint.merMod(sup.pers.m3.2, method = 'b', nsim = 999)

## Create Organized Table from These Effects
ranFX.m3s <- VarCorr(sup.pers.m3.1)
fixFX.m3s <- data.frame(fixef(sup.pers.m3.1))
ranFX.m3s <- data.frame(ranFX.m3s)[,c(1,4)]
row.names(ranFX.m3s) <- ranFX.m3s$grp
colnames(ranFX.m3s) <- c('grp', 'estimate')
colnames(fixFX.m3s) <- 'estimate'

sup.pers.booter1 <- rbind(sup.pers.boot3.1[c(1:2),]^2, sup.pers.boot3.1[c(3:9),])
est.m3s <- rbind(ranFX.m3s[2], fixFX.m3s)

ranFX.m2s <- VarCorr(sup.pers.m3.2)
fixFX.m2s <- data.frame(fixef(sup.pers.m3.2))
ranFX.m2s <- data.frame(ranFX.m2s)[,c(1,4)]
row.names(ranFX.m2s) <- ranFX.m2s$grp
colnames(ranFX.m2s) <- c('grp', 'estimate')
colnames(fixFX.m2s) <- 'estimate'

sup.pers.booter2 <- rbind(sup.pers.boot3.2[c(1:2),]^2, sup.pers.boot3.2[c(3:9),])
est.m2s <- rbind(ranFX.m2s[2], fixFX.m2s)

round(cbind(est.m3s, sup.pers.booter1), 2) # export to LaTeX
round(cbind(est.m2s, sup.pers.booter2), 2) # export to LaTeX

## LAGGED EFFECTS?
summary(sup.pers.m4.1 <- lmer(scale(s.sup.1) ~ scale(s.pow.C1) + scale(s.pow.X) +
                             scale(s.pow.C) + scale(s.sup) + scale(time.days) + scale(time.hour) +
                             (1 | idx), data = s1, REML = F))

summary(sup.pers.m4.2 <- lmer(scale(sup.1) ~ scale(pwst.C1) + scale(pwst.X) +
                             scale(pwst.C) +
                             (1 | idx), data = s2, REML = F))

summary(sup.pers.m3.1 <- lmer(scale(s.sup) ~ scale(s.pow.X1) + scale(s.pow.C1) +
                             scale(time.days) + scale(time.hour) +
                             (1 | idx), data = s1, REML = F))

### GRAPHS!!
names(s1)

s1 <- within(s1, s.power.X <- ave(s.pow, idx, FUN = function(x) mean(x, na.rm = T)))
s1 <- within(s1, s.status.X <- ave(s.stat, idx, FUN = function(x) mean(x, na.rm = T)))
s1 <- within(s1, s.power.C <- s.pow - s.power.X)
s1 <- within(s1, s.status.C <- s.stat - s.status.X)

summary(sup.power <- lmer(s.pow ~ s.sup.X + s.sup.C +
                         time.days + time.hour +
                         (1 | idx), data = s1, REML = F))

par(mfrow = c(1,2))
with(s1, plot(s.power.X ~ s.sup.X, xlab = "Stable Suppression", ylab = "Stable Power",
             xlim = c(1,5), ylim = c(1,5), pch = 19, cex = .8,
             main = ""))
abline(a = fixef(sup.power)[1], b = fixef(sup.power)[2], lty = 1, col = 'red', lwd = 4)

```

```

with(s1, plot(s.power.C ~ s.sup.C, xlab = "Contextual Suppression", ylab = "Contextual Power",
             xlim = c(-5,5), ylim = c(-5,5), pch = 19, cex = .8))
abline(a = 0, b = fixef(sup.power)[3], lty = 1, col = 'red', lwd = 4)

par(mfrow = c(1,2))
summary(wb.power <- lmer(s.WB ~ s.power.X + s.power.C +
                       time.days + time.hour +
                       (1 | idx), data = s1, REML = F))

with(s1, plot(s.WB.X ~ s.power.X, xlab = "Stable Power", ylab = "Stable Well-Being",
             xlim = c(1,5), ylim = c(1,5), pch = 19, cex = .8,
             main = ""))
abline(a = fixef(wb.power)[1], b = fixef(wb.power)[2], lty = 1, col = 'red', lwd = 4)

with(s1, plot(s.WB.C ~ s.power.C, xlab = "Contextual Power", ylab = "Contextual Well-Being",
             xlim = c(-5,5), ylim = c(-5,5), pch = 19, cex = .8))
abline(a = 0, b = fixef(wb.power)[3], lty = 1, col = 'red', lwd = 4)

#####
## Q3: Why Do People Vary in Suppression?      ###
#####

## Features of the Person
summary(sup.wellB.11 <- lmer(scale(s.WB) ~ scale(s.sup.C) + scale(s.sup.X) +
                           scale(time.days) + scale(time.hour) +
                           (s.sup | idx), data = s1, REML = F))

summary(sup.wellB.11 <- lmer(scale(s.WB) ~ scale(s.sup.C) + scale(s.sup.X) +
                           scale(time.days) + scale(time.hour) +
                           (s.sup | idx), data = s1, REML = F))

summary(sup.wellB.12 <- lmer(scale(s.WB) ~ scale(sup.X) + scale(sup.C) +
                           scale(day) + scale(hr) +
                           (sup | idx), data = s2, REML = F))

summary(sup.wellB.21 <- lmer(scale(s.WB) ~ (scale(s.sup.C) + scale(s.sup.X)) +
                           (scale(s.pow.C) + scale(s.pow.X)) +
                           scale(time.days) + scale(time.hour) +
                           (s.sup | idx), data = s1, REML = F))

summary(sup.wellB.22 <- lmer(scale(s.WB) ~ (scale(sup.C) + scale(sup.X)) +
                           (scale(pwst.X) + scale(pwst.C)) +
                           scale(day) + scale(hr) +
                           (sup | idx), data = s2, REML = F))

summary(sup.wellB.31 <- lmer(scale(s.WB) ~ (scale(s.sup.C) + scale(s.sup.X)) *
                           (scale(s.pow.C) + scale(s.pow.X)) +
                           scale(time.days) + scale(time.hour) +
                           (s.sup | idx), data = s1, REML = F))

summary(sup.wellB.32 <- lmer(scale(s.WB) ~ (scale(sup.C) + scale(sup.X)) *
                           (scale(pwst.X) + scale(pwst.C)) +
                           scale(day) + scale(hr) +
                           (sup | idx), data = s2, REML = F))

sup.wellB.boot11 <- confint.merMod(sup.wellB.11, method = 'boot', nsim = 999)
sup.wellB.boot12 <- confint.merMod(sup.wellB.12, method = 'boot', nsim = 999)

```

```

sup.wellB.boot21 <- confint.merMod(sup.wellB.21, method = 'boot', nsim = 999)
sup.wellB.boot22 <- confint.merMod(sup.wellB.22, method = 'boot', nsim = 999)
sup.wellB.boot31 <- confint.merMod(sup.wellB.31, method = 'boot', nsim = 999)
sup.wellB.boot32 <- confint.merMod(sup.wellB.32, method = 'boot', nsim = 999)

sup.wellB.boot11^2
sup.wellB.boot12^2
sup.wellB.boot21
sup.wellB.boot22
sup.wellB.boot31
sup.wellB.boot32

## Features of the Situation: Who they are with.

summary(sup.wellB.11 <- lmer(scale(s.WB) ~ scale(s.sup.C) + scale(s.sup.X) +
                           scale(time.days) + scale(time.hour) +
                           (s.sup | idx), data = s1, REML = F))

summary(sup.wellB.11 <- lmer(scale(s.WB) ~ scale(s.sup.X) + scale(s.sup.C) *
                           as.factor(socF) -1 +
                           scale(time.days) + scale(time.hour) +
                           (s.sup | idx), data = s1, REML = F))

summary(sup.wellB.12 <- lmer(scale(s.WB) ~ scale(sup.X) + scale(sup.C) * socF +
                           scale(day) + scale(hr) -1 +
                           (sup | idx), data = s2, REML = F))

# Features of the Situation: What they are doing.

summary(sup.sit.wb.m0.1 <- lmer(scale(s.WB) ~ scale(s.sup.X) + scale(s.sup.C) + (1 | idx), data = s1, REML =
F))
summary(sup.sit.wb.m1.1 <- lmer(scale(s.WB) ~ scale(s.sup.X) + scale(s.sup.C) + doF -1 + (1 | idx), data = s1,
REML = F))
summary(sup.sit.wb.m2.1 <- lmer(scale(s.WB) ~ scale(s.sup.X) + scale(s.sup.C) * doF -1 + (1 | idx), data = s1,
REML = F))
anova(sup.sit.wb.m1.1, sup.sit.wb.m2.1) # not significant

summary(sup.sit.wb.m0.2 <- lmer(scale(s.WB) ~ scale(sup.X) + scale(sup.C) + -1 (1 | idx), data = s2, REML = F))
summary(sup.sit.wb.m1.2 <- lmer(scale(s.WB) ~ scale(sup.X) + scale(sup.C) -1 + doF + (1 | idx), data = s2, REML
= F))
summary(sup.sit.wb.m2.2 <- lmer(scale(s.WB) ~ scale(sup.X) + scale(sup.C) * doF + -1 + (1 | idx), data = s2,
REML = F))
anova(sup.sit.wb.m1.2, sup.sit.wb.m2.2)

## Model Fit

Anova(sup.wellB.11)
Anova(sup.wellB.12)

vif.mer(sup.wellB.11)
vif.mer(sup.wellB.12)

#####
# GRAPHS!
#####
par(mfrow = c(1,2))
# Model 1: Sample 1

```

```

fixef(sup.wellB.11)
with(s1, plot(scale(s.WB.X) ~ scale(s.sup.X), xlab = "Stable Suppression", ylab = "Stable Well-Being",
             xlim = c(-3,3), ylim = c(-3,3), pch = 19, cex = .8,
             main = ""))
abline(a = fixef(sup.wellB.11)[1], b = fixef(sup.wellB.11)[3], lty = 1, col = 'red', lwd = 4)

with(s1, plot(s.WB.C ~ s.sup.C, xlab = "Situational Suppression", ylab = "Situational Well-Being",
             xlim = c(-5,5), ylim = c(-5,5), pch = 19, cex = .8))
abline(a = fixef(sup.wellB.11)[1], b = fixef(sup.wellB.11)[2], lty = 1, col = 'red', lwd = 4)

# Model 2: Sample 1
## Create residual variables to estimate unique effects of suppression on well-being:

### Estimate effect of power on suppression & well-being
mod1 <- lm(s.sup.X ~ s.pow.X, data = s1, na.action=na.exclude)
mod2 <- lm(s.WB.X ~ s.pow.X, data = s1, na.action=na.exclude)

mod3 <- lmer(s.sup.C ~ s.pow.C + (1 | idx), data = s1, na.action=na.exclude)
mod4 <- lmer(s.WB.C ~ s.pow.C + (1 | idx), data = s1, na.action=na.exclude)

### Save residuals from above models as a new variable.

s.sup.X2 <- residuals(mod1)
s.WB.X2 <- residuals(mod2)

s.sup.C2 <- residuals(mod3)
s.WB.C2 <- residuals(mod4)

## Graph these residual scores
fixef(sup.wellB.21)
plot(s.WB.X2 ~ s.sup.X2, xlab = "Stable Suppression", ylab = "Stable Well-Being",
     xlim = c(-2,2), ylim = c(-2,2), pch = 19, cex = .8,
     main = "")
abline(a = fixef(sup.wellB.21)[1], b = fixef(sup.wellB.21)[3], lty = 1, col = 'red', lwd = 4)

plot(s.WB.C2 ~ s.sup.C2, xlab = "Situational Suppression", ylab = "Situational Well-Being",
     xlim = c(-5,5), ylim = c(-5,5), pch = 19, cex = .8)
abline(a = fixef(sup.wellB.21)[1], b = fixef(sup.wellB.21)[2], lty = 1, col = 'red', lwd = 4)

# Model 3 (Interaction Plots); Sample 1
fixef(sup.wellB.31)
plot(s.WB.X2 ~ s.sup.X2, xlab = "Stable Suppression", ylab = "Stable Well-Being",
     xlim = c(-2,2), ylim = c(-2,2), pch = 19, cex = .8,
     main = "")
abline(a = (fixef(sup.wellB.31)[1] + fixef(sup.wellB.31)[5]),
       b = (fixef(sup.wellB.31)[2] + fixef(sup.wellB.31)[11]), lty = 1, col = 'red', lwd = 3) # High Power
abline(a = (fixef(sup.wellB.31)[1] - fixef(sup.wellB.31)[5]),
       b = (fixef(sup.wellB.31)[2] - fixef(sup.wellB.31)[11]), lty = 2, col = 'red', lwd = 3) # Low Power

plot(s.WB.C2 ~ s.sup.C2, xlab = "Situational Suppression", ylab = "Situational Well-Being",
     xlim = c(-5,5), ylim = c(-5,5), pch = 19, cex = .8)
abline(a = (fixef(sup.wellB.31)[1] + fixef(sup.wellB.31)[4] + fixef(sup.wellB.31)[4]),
       b = (fixef(sup.wellB.31)[2] + fixef(sup.wellB.31)[8]), lty = 1, col = 'red', lwd = 3) # High Power
abline(a = (fixef(sup.wellB.31)[1] - fixef(sup.wellB.31)[4]),
       b = (fixef(sup.wellB.31)[2] - fixef(sup.wellB.31)[8]), lty = 2, col = 'red', lwd = 3) # Low Power

#####
## Discriminant Analyses

```

```

## NOT EXTRAVERSION.
summary(sup.wellB.X11 <- lmer(scale(s.WB) ~ (scale(s.sup.C) + scale(s.sup.X)) *
  (scale(s.pow.C) + scale(s.pow.X)) +
  scale(s.e.X) + scale(s.e.C) +
  scale(time.days) + scale(time.hour) +
  (s.sup | idx), data = s1, REML = F))

summary(sup.wellB.X12 <- lmer(scale(s.WB) ~ (scale(sup.C) + scale(sup.X)) *
  (scale(pwst.X) + scale(pwst.C)) +
  scale(e.X) + scale(e.C) +
  scale(day) + scale(hr) +
  (sup | idx), data = s2, REML = F))

summary(sup.wellB.X21 <- lmer(scale(s.WB) ~ (scale(s.sup.C) * scale(s.e.C)) +
  (scale(s.sup.X) * scale(s.e.X)) +
  scale(time.days) + scale(time.hour) +
  (s.sup | idx), data = s1, REML = F))

summary(sup.wellB.X22 <- lmer(scale(s.WB) ~ (scale(sup.C) * scale(e.C)) +
  (scale(e.X) * scale(sup.X)) +
  scale(day) + scale(hr) +
  (sup | idx), data = s2, REML = F))

## WELL-BEING DOESN'T MODERATE THE RELATIONSHIP BETWEEN SUPPRESSION & POWER
summary(sup.wellB.X31 <- lmer(scale(s.pow) ~ (scale(s.sup.C) * scale(s.WB.C)) +
  (scale(s.WB.X) * scale(s.sup.X)) +
  scale(time.days) + scale(time.hour) +
  (s.sup | idx), data = s1, REML = F))

summary(sup.wellB.X32 <- lmer(scale(pwst) ~ (scale(sup.C) * scale(s.WB.C)) +
  (scale(s.WB.X) * scale(sup.X)) +
  scale(day) + scale(hr) +
  (sup | idx), data = s2, REML = F))

## DOES IT LAG??
summary(sup.wellBS1C <- lmer(scale(s.WB.T1) ~ scale(s.sup.X) +
  (scale(s.sup.C1) * scale(s.pow.C1)) +
  (scale(s.sup.C) * scale(s.pow.C)) +
  scale(s.pow.X) + scale(time.days) +
  scale(time.hour) + (s.sup | idx),
  data = s1, REML = F))

summary(sup.wellBLag1 <- lmer(scale(s.WB.T1) ~ scale(s.sup.X) +
  (scale(s.sup.C) * scale(s.pow.C)) +
  (scale(s.sup.C1) * scale(s.pow.C1)) +
  scale(s.pow.X) + scale(s.WB) +
  scale(time.days) + scale(time.hour) +
  (s.sup | idx), data = s1, REML = F))

summary(sup.wellBLag2 <- lmer(scale(WB.T1) ~ scale(sup.X) + scale(sup.C1) + scale(sup.C) +
  (sup | idx), data = s2, REML = F))

# LAGGED VARIABLES
s1 <- s1[with(s1, order(idx, code.time)),]

s1$s.WB.T1 <- matrix(data = NA, nrow = nrow(s1), ncol = 1)
s1$s.sup.1 <- matrix(data = NA, nrow = nrow(s1), ncol = 1)
s1$s.sup.X1 <- matrix(data = NA, nrow = nrow(s1), ncol = 1)

```



```

s1$s.pow.X1 <- matrix(data = NA, nrow = nrow(s1), ncol = 1)
s1$s.sup.C1 <- matrix(data = NA, nrow = nrow(s1), ncol = 1)
s1$s.pow.C1 <- matrix(data = NA, nrow = nrow(s1), ncol = 1)

s1$idx <- as.factor(s1$idx)

for (i in 1:length(levels(s1$idx))) {
  s1[s1$idx == i,]$s.sup.1 <- with(s1[s1$idx == i,], c(rep(NA, 1), s.sup)[1 : length(s.sup)])
}

for (i in 1:length(levels(s1$idx))) {
  s1[s1$idx == i,]$s.WB.T1 <- with(s1[s1$idx == i,], c(rep(NA, 1), s.WB)[1 : length(s.WB)])
}

for (i in 1:length(levels(s1$idx))) {
  s1[s1$idx == i,]$s.sup.X1 <- with(s1[s1$idx == i,], c(rep(NA, 1), s.sup.X)[1 : length(s.sup.X)])
}
for (i in 1:length(levels(s1$idx))) {
  s1[s1$idx == i,]$s.pow.X1 <- with(s1[s1$idx == i,], c(rep(NA, 1), s.pow.X)[1 : length(s.pow.X)])
}
for (i in 1:length(levels(s1$idx))) {
  s1[s1$idx == i,]$s.sup.C1 <- with(s1[s1$idx == i,], c(rep(NA, 1), s.sup.C)[1 : length(s.sup.C)])
}
for (i in 1:length(levels(s1$idx))) {
  s1[s1$idx == i,]$s.pow.C1 <- with(s1[s1$idx == i,], c(rep(NA, 1), s.pow.C)[1 : length(s.pow.C)])
}

##### STUDY TWO
## Fill in missing data to create lagged variable.
time.frame2 <- data.frame(idx = rep(1:length(levels(s2$idx)), each = 36),
                          time = rep(1:36))
nrow(time.frame) - length(levels(s2$idx)) * 36 # making sure it is the right length.
s2 <- merge(s2, time.frame2, by = c('idx', 'time'), all.y = T)

nrow(s2) # making sure it's the right length.

## Create Lagged Effects
s2 <- s2[with(s2, order(idx, time)),] # sort dataframe by id, then time.

# create shell for time-lagged variables.
s2$WB.T1 <- matrix(data = NA, nrow = nrow(s2), ncol = 1)
s2$sup.1 <- matrix(data = NA, nrow = nrow(s2), ncol = 1)
s2$sup.C1 <- matrix(data = NA, nrow = nrow(s2), ncol = 1)
s2$pwst.C1 <- matrix(data = NA, nrow = nrow(s2), ncol = 1)
s2$idx <- as.factor(as.numeric(as.factor(as.character(s2$idx))))

## Create time-lagged variable.
for (i in 1:length(levels(s2$idx))) {
  s2[s2$idx == i,]$sup.1 <- with(s2[s2$idx == i,], c(rep(NA, 1), sup)[1 : length(sup)])
}
for (i in 1:length(levels(s2$idx))) {
  s2[s2$idx == i,]$WB.T1 <- with(s2[s2$idx == i,], c(rep(NA, 1), s.WB)[1 : length(s.WB)])
}
for (i in 1:length(levels(s2$idx))) {
  s2[s2$idx == i,]$sup.C1 <- with(s2[s2$idx == i,], c(rep(NA, 1), sup.C)[1 : length(sup.C)])
}
for (i in 1:length(levels(s2$idx))) {
  s2[s2$idx == i,]$pwst.C1 <- with(s2[s2$idx == i,], c(rep(NA, 1), pwst.C)[1 : length(pwst.C)])
}

```

Vita

Arman Daniel Catterson was born in Austin, Texas on July 3, 1986 to Shirin Khosropour and Donald Edwin Catterson. Daniel grew up in Austin, attended Stephen F. Austin High School, and graduated with a B.A. from the University of Texas at Austin. He majored in Psychology as a Plan II Honor's student, and worked with Dr. Sam Gosling on a thesis project to examine the accuracy of personality impressions among friends who only knew each other from online interactions. In 2008 he began his graduate training at the University of California, Berkeley with Dr. Oliver P. John. In early 2012, he married Amy Elizabeth Koehler. In the summer of 2013, he worked at Google as a People Analyst. In the fall of 2013 he started to learn guitar. After graduating from Berkeley in May 2015, Daniel will lecture at UC Berkeley and Berkeley City College, research at the Institute for Personality and Social Research at Berkeley, consult with a company in Emeryville, and continue to live in Oakland, CA with his wife and cat.