Possessions and the Self: Downstream Consequences of
Ownership and Sharing What We Own

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ABSTRACT

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My dissertation is based on the premise that possessions are an extension of the self. Beyond simple functional benefits that possessions provide us, I question whether possessions affect our self-perception and behavior. Specifically, I focus on two aspects of possessions: Ownership (Essay 1) and Sharing (Essay 2). In Essay 1, I find that feeling a sense of product ownership has downstream consequences in one's representation of who s/he is. Here I reveal that salient feelings of product ownership activate a product-related self in one's mind, but more importantly deactivate product-unrelated self. By identifying simultaneous identity activation and deactivation, I show that an individual can only hold a limited number of salient selves, and activating one's self aspect requires a trade-off. This finding updates the prior assumption in the literature that an individual can hold an unlimited number of selves, and further suggests that there is still a finite limit to what can be salient at a given time.

My interest in ownership extends to Essay 2, where I examine another behavioral aspect of consumers: sharing. Sharing behavior has received much attention lately due to the rise of sharing economy platforms, which provide new opportunities for consumers to share personal belongings with others. In Essay 2, I mine people's latent motivation behind sharing by using a transaction dataset from one of the largest sharing economy platforms, Airbnb. Here I find that people are driven by not only monetary, but also non-monetary reasons, such as desires to meet others and share the beauty of their homes. Then I explore how each motivation affects people's

engagement on the sharing economy platform and their continued effort to share. This second essay highlights individuals' new role as micro-entrepreneurs in this new era of the 21st century.

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DEDICATION

To my little treasure, Ayn.

It is my greatest blessing to be your mom.

I pray and bless you that God leads your way, as He has led my way.

CHAPTER 1

INTRODUCTION

Each day is filled with opportunities to own more. From Valentine's Day, Memorial Day, Labor Day, Thanksgiving, Christmas, and back to New Year's Eve, each holiday and weekend is filled with endless opportunities for bargains and sales. Colorful and persuasive advertisements are inserted every few minutes in between our favorite TV shows, and people look forward to watching newly released commercials during Super Bowl season. Birthdays are often paired with gifts and goodie bags. Halloween is about purchasing large bags of candy at Costco and costumes at pop-up stores on streets. Thanksgiving Day is paired with Black Friday deals, where people wait in long lines from early dawn. Preparation for Christmas starts right after Thanksgiving, when parents purchase freshly cut trees from open-markets and carry them home. The highlight of Christmas is when kids gather together under the tree to unwrap gift boxes. A strong relationship with possessions is built from an early age. Children learn to understand a sense of ownership over their toys, asking if they can "borrow" someone else's and fighting over who owns what. As a result, our closets, desk drawers, homes, and offices are filled with possessions. Possessions have become an essential component of our lives.

We live in a world where we continuously interact with our possessions. Here, possessions influence and form people's self-views, behaviors, and performances. Consider an example of a male accountant who owns a Toyota Land Cruiser, a jeep-like SUV that has off-road prowess and bold exterior details with strong engine power. This car lets the accountant feel a sense of empowerment and strength. While it is not new for a consumer to embrace product traits, what has not been examined is whether possessions also make a person "less" like another

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kind of self. For example, does owning a Land Cruiser affect the man's self-view as an accountant or a dad? Furthermore, does it also affect his ability to perform in tasks related to accounting or parenting?

Now, consider another situation where the same owner of a Land Cruiser downloads a car-sharing app (e.g., Uber/ Lyft), and uses it during weekends to give rides to others. He might be simply interested in earning extra cash, but he might also be enjoying the experience of sharing rides in his favorite car with others. In this case, that owner is not exclusively using the car for himself, but he is sharing the "Land Cruiser ride experience" with other people. This action may be driven by his non-monetary motivation and by his intrinsic joy of sharing. This makes the possession no longer exclusive, but inclusive. The relationship between owner-possession becomes dynamic.

Together, my dissertation examines the topic of product ownership and sharing. Specifically, my first essay examines the topic of ownership and investigates the downstream consequences of possessions affecting owners' behaviors. Here, I propose that possession not only activates, but more importantly, also deactivates different aspects of the self with downstream consequences on performance enhancement and impairment in different tasks. While there has been prior research indicating that possessions activate certain aspects of the self, no research has relied on the premise that one's self-concept is limited, such that activating a product-related self could simultaneously mean deactivating a product-unrelated self. This argument suggests that not all self-aspects are salient at the same time, and that a greater representation of one self-aspect suppresses the representation of another self-aspect.

In the second essay, I examine the topic of sharing and investigate how different motivations give rise to different sharing behaviors. This essay reflects on a recent trend of

technological advancement, in which owners can share their possessions with others using sharing-economy platforms, such as Airbnb. Unlike the traditional economy where firms provide goods and people consume goods, individuals have the opportunity to share their possessions in return for a fee. Here, firms help these individuals connect with each other by providing online platforms and receiving a small fraction of the fee. While the traditional economy is run by firms' primary goal to make revenue, the sharing economy differs in that individuals may have several motivations behind their sharing behavior. Granted, some may only be interested in making a financial profit, but I demonstrate that others may be interested in sharing desirable features of their possessed goods (like the example of a Land Cruiser) or simply to meet new people. This sharing behavior is growing and the sharing economy market is now competing with a traditional market. My dissertation examines how different motivations can give rise to this sharing intention, as well as consumers' continued likelihood to share (i.e., retention).

My research on ownership shares roots with my interest in self-identity. This is because possessions are intimately interwoven into people's understanding of who they are and possessions often reflect people's current state, desires, motives and components of the self. Next, I will first review previous literature on a multi-faceted aspect of the self, then describe the literature on ownership and sharing. Building on prior literature, I will describe how my two essays distinctively contribute to the field of marketing and psychology.

CHAPTER 2

LITERATURE REVIEW

2.1. Multi-facets of the Self

The dynamic self. While the prior belief about the self was that it is a cluster of different individual traits, additional evidence suggests that the self is constructed of a sophisticated cognitive structure (McConnell and Strain 2007). In fact, an individual's self-concept is vast and multi-faceted (Markus and Kunda 1986; McConnell and Strain 2007) – it holds different goals, evaluations, behaviors, and beliefs that may potentially go with or against each other (Greenwald and Pratkanis 1984; Markus and Wurf 1987; Sorrentino and Higgins 1986). Within the self-structure, people experience differing levels of connectedness to several aspects of their identities (Bartels and Urminsky 2011).

The self-structure is not only consistent with the current self-view, but also includes cognitive components of hopes, desires, and goals for the future. When the future self is the desired self, the current self aims for achieving the future self. A person can shed the present self and persistently try to pursue the attainable future self (Oyserman and James 2011). The self-structure is also composed of not only the present and future selves, but also past selves that guide an individual's perception and understanding of the current environment (Markus 1977). A number of selves dwindle with time: with new selves arising, possible and desired future selves guide the direction of the current self. It is also possible that different self-components result in self-conflict, self-distortion, and dilemma (Markus and Nurius 1986). This makes people seek a resolution to maintain a coherent self. For example, one study revealed that when people are tempted to behave dishonestly, they do so up to the degree to which they could delude

themselves at a justifiable level to maintain an honest self-view (Mazar, Amir, and Ariely 2008). People can choose what identities to pursue and decide the level and the strength of the pursuit.

The inter-relationship of several selves. Among the complex structure of the self, circumstances and environmental cues can activate a subset of the self (Mandel 2003; Oyserman 2009; Oyserman and James 2011). The activation of one self (e.g., Being a triathlon) can also activate a related, but different self (e.g., Being a Navy Seal), and the activation of different selves can be bi-directional (McConnell 2011). This concept is similar to the well-established literature in cognitive psychology, (Hertz, Krogh, and Palmer 1991; McClelland and Rumelhart 1981) where different conceptual nodes are interconnected, and activating one node also activates connected nodes. The spreading activation is observed among nodes that share similar traits, and this depends on how nodes are structured and patterns between those nodes (Read, Vanman, and Miller 1997). Similarly, a related set of identities can activate one another.

People also shift between different selves. For example, one study shows that when individuals were reminded of their interdependent identity, they were more likely to seek risks because they perceived interpersonal relationship (i.e., their social network) as a buffer to the negative outcome. On the other hand, when individuals who shifted their self-view in the frame of mind of someone who is independent, they were less likely to seek such risks (Mandel 2003). Importantly, this example suggests that different self-representations compete with one another. A small but growing argument suggests that dominant self-view suppresses the other self-views (Macrae, Bodenhausen, and Milne 1995). The non-dominant self-views are not passively decayed, but are actively inhibited. Inhibiting the self is beneficial because it helps the self to maintain a coherent and stable self-concept (Bodenhausen, Macrae, and Hugenberg 2003), and to maintain a legitimate and fair external system (Wu, Cutright, and Fitzsimons 2011). This

argument is partly supported by negative priming in cognition literature. The literature suggests that attention to a focal object leads to ignorance, and even suppression of other targets because this helps an individual to better process the target (Neumann and Deschepper 1992). Research on (de)valuation also supports this view by suggesting that an activation of a target need (e.g., eating) devaluates other unrelated needs (e.g., taking shower; Brendl, Markman, and Messner 2003).

Applying this insight to the self-identity literature, some initial evidence suggests that the suppression is observed in people's tendency to suppress conflicting self-view. For example, when fraternity/sorority members were reminded of their "Greek" identity, they mentally deactivated their self-view as university students below the baseline (Hugenberg and Bodenhausen 2004). Building on this growing evidence, my dissertation further suggests that identity deactivation can occur among not only conflicting, but also unrelated identities.

Measuring identity. Measuring identity activation is often challenging, because identity activation is not necessarily explicit and operates primarily at implicit levels (Lane and Scott 2007; Oyserman 2009). Because of this, researchers have used both explicit self-report questionnaires and implicit questionnaires to measure identity activation. One of the common implicit measurements is the implicit association task (IAT), where researchers measure keyboard response speed to examine how strongly participants associate different words. For example, when female participants are primed (vs. not primed) with gender identity, they are quicker to associate the word "art" with the word "pleasant", and "math" with the word "unpleasant" (Steele and Ambady 2006). Another similar implicit measurement is the lexical decision task that also measures users' response speed, where participants press a "yes" key for the traits they perceive as a description of the self, while pressing a "no" key for traits that are

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not a good description of the self (Coats et al. 2000). There are also simpler measurements than measuring response speed. The word completion task is one, in which participants fill out word fragments that could be completed with different answers. For example, the word fragment "(UNI_ _ _)" could either be related to the independent self "(UNIQUE)" or the interdependent self "(UNITED)" (Johnson and Lord 2010). Researchers also use a twenty-statement task where participants fill in statements that start with "I am _____". Here, the proportion of a target identity (e.g., academic self: statistician, researcher, student, teaching assistant) that appears among the 20 statements is used to examine the degree of identity salience within an individual (Kuhn and McPartland 1954).

2.2 The Relationship between Self-concept and Product Consumption

Industrialization and urbanization have replaced community and tradition (Cushman 1990). This new social standard calls for a new set of values and ideals, which ultimately affects how people construct and maintain their self-view. The desire for a healthy and coherent self is now satisfied through advertising and product consumption as commercialism kicks in to signal and emphasize the desired social values (Shepherd, Chartrand, and Fitzsimons 2015). The acquisition and usage of consumer products have replaced the role of self-actualization (Cushman 1990). This, as a result, has led to a more intimate relationship between the self and the product. In a consumption society in which brands and services blanket the marketplace, possessions often trigger a specific subset of the self, and people use these possessions to communicate to others, to reach for self-growth, and to repair and actualize the self (Lifton 1971).

Possession is embraced into one's identity. Whether it be intentional or not, consumers choose products to highlight their value system (ex. wearing a cross necklace for religious symbolism), or to represent their self-view in a certain way (ex. using apple products to be seen as a hipster). Furthermore, consumers use products to communicate their beliefs and various social affiliations (Wu, Cutright, and Fitzsimons 2011). Possessions also serve to amplify a positive current self-image (Beauregard and Dunning 2001; Sirgy 1982) and to pursue an idealized self-image (Bagwell and Bernheim 1996; Escalas and Bettman 2005). People may differ in their tendency to embrace brands close to their self-concept. So much so that a marketing scale, "brand engagement in self-concept," was developed to measure individual differences in brand engagement (ex: "I have a special bond with the brands that I like", "My favorite brands are an important indication of who I am") (Sprott, Czellar, and Spangenberg 2009).

Receiving gifts from friends, prizes from radio programs, giveaways from manufacturers, or inherited objects can also transfer the product traits to the self (Huang, Wang, and Shi 2009). Nowadays, the desire for self-representation also extends to the digital world where web space, such as Facebook, Instagram, and personal websites are constructed and filled with filtered, photo-shopped images and impactful affective texts. These have now all become a composite of their self-possessions in the online space (Schau and Gilly 2003).

Given the wide array of possessions that people have, do people experience a sense of ownership of each and every possession? Do all possessions always and simultaneously activate different selves? Is it necessary for people to legally own a product to elicit certain self-view? Or is it possible for a subset of the self to remain activated even when a consumer does not legally

own a product? To answer this question, let's turn to the concept of legal and psychological ownership.

2.3. Legal and Psychological Ownership

Legal ownership is recognized by society and gives an individual the right to possess a product with legal protection (Pierce, Kostova, and Dirks 2003). Legal ownership can elicit the feeling that a product is a part of the self, thereby activating the product-related self in one's mind. However, owning a product does not necessarily mean that legal owners find a personal connection to every object they own, and feel that the product is "mine" (McCracken 1986). While there are more than a few hundred products an individual owns from a car, laptop, uniform, hanger, or basket to a kitchen towel, not all products always are viewed as a part of the self. Some items- usually more symbolic ones, such as cars or uniforms are likely to convey more salient self-meanings, and thereby compose an important role in defining the self (Berger and Heath 2008).

It is also possible that people feel that certain products define themselves, even when they do not own the product. People can experience psychological ownership without legal ownership (Furby 1991; Pierce, Kostova, and Dirks 2003). And this psychological ownership is enough to make a person feel that a product is part of the self. For example, recent research has shown that a mere touch or mental imagery of a product is enough to increase feelings of psychological ownership (Peck and Shu 2009). Employees can also experience feelings of ownership at their workplace (Pierce, Kostova, and Dirks 2001), or it can be experienced by nonphysical entities, such as ideas or words that one generates (Isaacs 1933). For example, a girl who sings Frozen may feel that the song is hers and object to the idea that her peer might sing the same song.

Likewise, both legal and psychological ownership elicit a product-related self-view in one's mind. With growing interests in the concept of a product composing an important part of self-identity, Weiss and Johar (2013) developed a "part-of-self" scale. The part-of-self scale measures the extent to which a consumer classifies an object and its associated characteristics as his or her personal-self ('me') while classifying the remaining objects as not part of the personal self ('not-me'). To measure the degree of product-self association, the scale describes the following: "If you think of all the objects (or, replaceable with *object-related traits*) in the world, you may notice that they can be classified into two groups: the object that you classify as being part of yourself and the rest of the objects, which are not part of yourself. For different people, each category (part of my self vs. not part of my self) is comprised of different objects. This feeling of psychological ownership measurement is object-specific and does not necessarily generalize to 'all possessions' (i.e., mine is me) (Weiss and Johar 2013). For example, a consumer may experience that a MacBook is an important part of the self, while not necessarily feeling the same about his kitchen utensils. That is, the scale appraises the degree to which certain product-related identity becomes more salient in one's representation of his or her self.

Whether it be legal or psychological, the feelings of ownership make people feel that product characteristics composite an important part of their self-identity (Pierce, Kostova, and Dirks 2001, 2003; Turk et al. 2011; Weiss and Johar 2013). These consumers experience mental synthesis between a product and the self – their skewing value and valence reflect that these products comprise an important element of the self (Knetsch and Sinden 1984; Mann 1991; Turk et al. 2011). Using this construct, my first essay examines both legal and psychological ownership, and suggests that both can activate a product-related self in one's mind. The second essay focuses on legal ownership, in which home owners share their homes with others.

2.4. Owning Possessions: Downstream Consequences

Embracing products into self-identity is observed in various forms around us: homes, new cars, good furniture, the latest electronic appliances or even the neighborhood (Belk 1988). Then, what are the behavioral downstream effects of psychological ownership? A growing number of papers demonstrate that feeling psychological ownership can form consumers' perceptions and behaviors, and even help achieve their desired self. For example, beginner tennis players with great commitment to learn new skills exhibited greater brand connections than both beginner tennis players with less commitment, and expert tennis players. Similarly, first-year students owned more items with printed university logos than senior students at a university (Braun and Wicklund 1989). Consumers also purchase unnecessary, luxury products because it helps an individual to symbolically achieve the desired self and to reconcile the self-discrepancy (Kim and Rucker 2012). Overall, a growing number of findings demonstrated that products help people repair and project the desired self by assimilating to the symbolic value of their possessions (Weiss and Johar 2013).

Possessions and the self are intimately interwoven such that arbitrarily removing such possessions may even negatively affect one's psychological well-being. For example, Cram and Paton (1993) noted that seniors who move out from their homes to nursing facilities usually experience a significant level of frustration as they are separated from their possessions – home, furniture and belongings. Consumers who identify certain products as their identity are likely to be loyal to the product, resist adopting unfamiliar products (Lam et al. 2010), and equate threat to a brand of a product as a threat to their identity (Lisjak, Lee, and Gardner 2012).

On the other hand, there are also situations in which consumers willingly disassociate themselves from their identity-linked products. For example, when students learned that their

own school ranked poorly in comparison to other schools, they experienced self-threat and those students with interdependent-mindset were less likely to choose a product with their university logo (White, Argo, and Sengupta 2013). Likewise, consumers associate and disassociate themselves from products because they have a goal to maintain a positive and consistent self-view.

2.5. Sharing Possessions: Behavioral Consequences

Consumers not only own but also share their possessions. With increasing opportunities to connect with others using sharing economy firms such as Airbnb and Uber, owners can now share their possessions with strangers. Despite the accelerating growth of sharing economy firms, not much research has yet examined the antecedents and the consequences of sharing. For example, what are the latent motivations that guide the sharing decision? How do different latent motivations affect each individual's behavior, in terms of their engagement and continued willingness to share (i.e., retention likelihood)?

There is a small but growing amount of research on sharing, with much focus on defining what the sharing economy is. The discussion centers on defining the concept with a common agreement that it is a non-ownership based economy. Based on this agreement, several similar concepts are introduced and used interchangeably in the field such as accessed-based-economy, peer-to-peer consumption, and collaborative consumption. Not much agreement has yet been made on what constitutes the necessary components for this new economy. Some argue that access-based goods, such as Zipcar, are an example of the sharing economy, while others include examples of sharing intangible goods, such as Wikipedia knowledge (Lakhani and Wolf 2003; Nov 2007). Others say that non-monetary based consumption such as Couchsurfing is an example of this industry (Lamberton 2015). While the focus of my dissertation is not to argue

what the right level of definition is for sharing economy, I specifically focus on contexts where (1) an owner provides service goods, as opposed to firms providing service goods (e.g., zipcar) (2) a possessed good is a non-duplicable tangible good as opposed to an intangible good (e.g., knowledge, music files), and situations where (3) financial transaction is involved.

Only a few researchers have started to investigate why people share their possessions. Research agrees that people are not merely driven by monetary reasons, and that several other motivations exist, such as the enjoyment of sharing, feelings of contribution to society, the desire to be more environmentally friendly, or valuing experiences over possessions (van der Heijden 2004; Lamberton 2016). Research also argues that monetary transaction is not necessarily the primary motivation, and that the transaction itself provides an assurance structure that allows both the owners (who are sharing their goods) and the consumers (who are using the goods) to facilitate social exchange (Lampinen and Cheshire 2016). This financial benefit does not necessarily crowd out the joy of social benefits, such as reciprocity, and can be a facilitator for sharing.

Next, I will describe two essays which focus on the owning (essay 1) and sharing (essay 2) of possessions. Specifically, Essay 1 examines how possessions not only activate, but also deactivate different aspects of the self with downstream consequences on performance in different domains. Essay 2 examines what motivates people to share their possessions in the context of Airbnb homes and explores the downstream consequences of these motivations in host engagement. In both essays, I bring in multiple methodologies, from lab experiments to text-mining and latent attrition models, thereby providing insights on how a diverse set of methodological tools can be utilized in consumer behavior research.

CHAPTER 3

ESSAY 1: THE SEESAW SELF: POSSESSIONS, IDENTITY (DE)ACTIVATION AND TASK PERFORMANCE

ABSTRACT

Research has shown that possessions have the power to change consumers' self-construal and activate different aspects of the self. Building on this literature, we suggest that the salience of product ownership not only activates the product-related self, but also simultaneously deactivates product-unrelated selves, resulting in impaired performance on tasks unrelated to the activated self. In five experiments, we first elicit feelings of ownership over a product (e.g., a calculator) to activate a product-related identity (e.g., the math self). Participants then engage in a task that is labeled as being a product-related task (e.g., math task) or a product-unrelated task (e.g., visual task). Despite the task being the same, participants in the ownership condition perform worse on a task labeled as product-unrelated than those in the baseline condition. Support for the underlying identity activation process comes from the finding that performance impairment is more likely to hold under conditions of low self-concept clarity, where identity is malleable. We discuss the theoretical and practical implications of this finding. (166 words)

3.1. Introduction

Teenagers purchase Nike shoes believing that they can be better athletes when they are wearing these shoes. Prospective job candidates wear designer suits believing that they will sound more sophisticated and impressive during an interview. Are consumers' intuitions regarding this influence of products and brands on their performance accurate? Recent research suggests that there are two ways in which brands and products can facilitate product-related performance. First, brand use can increase perceptions of domain specific self-efficacy and thereby enhance performance (Park and John 2014). Second, feelings of ownership over products can result in these products being categorized as a part-of-the-self and thereby affect product-related judgments and behaviors (Weiss and Johar 2016). An equally important, but unaddressed question, concerns consumer performance on product-unrelated tasks when product-related identity is activated. Would wearing a new pair of Nike shoes affect the teenager's ability to perform in non-athletic domains, such as in an English class? Or would purchasing a designer suit on a Saturday evening affect the job candidate's ability to cook dinner that night?

The current research examines downstream consequences of product ownership on task performance in product-unrelated domains. Consistent with prior research, we suggest that feelings of ownership can improve consumers' performance in product-related domains by activating the product-related identity. Importantly, we propose a novel by-product of such activation. We suggest that activating the product-related identity is likely to simultaneously deactivate product-unrelated identities and hence, impair consumers' performance in product-unrelated domains. It is well established that feelings of psychological ownership over a product activate product-related identity (Peck and Shu 2009; Weiss and Johar 2013), but we are not aware of any evidence for the deactivation of product-unrelated selves. We base our proposition

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on research suggesting that activation of one aspect of the identity can lead to a momentary deactivation of other aspects of the identity (Bodenhausen, Macrae, and Hugenberg 2003; Hodges and Park 2013; Zhang et al. 2013).

Our research contributes to the existing literature on identity from a theoretical as well as practical perspective. Theoretically, we propose that activating one identity can simultaneously deactivate other identities that may be unrelated (but not necessarily conflicting) to the activated identity. To our knowledge, such an assertion has not been made previously in the literature. Our experimental evidence is robust and reveals these effects with a simple change in task label while keeping the actual task the same. Individuals do not appear to consciously disengage from tasks unrelated to the currently active identity; rather, these effects appear to manifest outside of conscious awareness.

Practically, we show that the mere salience of possessions can lead to such identity activation and deactivation effects. Everyday activities such as shopping can activate product-related identities and deactivate product-unrelated ones, resulting in downstream consequences for consumer performance and behavior. In some domains such as education or gaming, task performance could be a critical variable that companies aim to maximize. Other than student learning being the singular goal of education, better performers (e.g., those who score higher on tests) are more likely to stay engaged and complete the course. Direct evidence for the relationship between performance and customer retention comes from online course providers ("MOOC Research - What We Know So Far" 2017). While it is impossible to disentangle causality in the relationship between student engagement and performance, it appears that they mutually reinforce each other. In fact, gaming companies design games to fit the level of the player to maintain a balance between challenge and achievement (Engeser and Rheinberg 2008).

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Gamers may be demotivated if the game is either too easy or too difficult. To enhance task performance and the perception of flow, identity activation may be a useful strategy that firms can employ. The notion of identity deactivation and performance impairment suggests that courses be maintained within portfolios of identity-related content and customers be encouraged to work within a skill domain at a time. We return to the practical relevance of our findings in the General Discussion section.

Possessions and Identity (De)Activation

Products are an integral part of consumers' identity (Reed et al. 2012). Our possessions communicate our social beliefs (e.g., breast cancer awareness bracelet) and our social affiliations (e.g., university t-shirts; Wu, Cutright, and Fitzsimons 2011). Possessions help individuals to explore and discover their identity (Wu, Cutright, and Fitzsimons 2011) or to pursue an idealized self-image (Mandel, Petrova, and Cialdini 2006). Consistent with the idea that products can activate aspects of identity, recent research has shown that feelings of product ownership lead to incorporating product attributes as a part-of-the-self (Weiss and Johar 2013). Such psychological ownership – the feeling that a product is part of the self – can arise without actually possessing a product, and by mere touch or mental imagery (Peck and Shu 2009). The sense of ownership can even be experienced in a virtual world and a product can be perceived as an extension of the self (Slater et al. 2009). What are the downstream behavioral consequences of feelings of ownership and identity activation?

Feelings of product ownership can lead consumers to behave in ways that are consistent with owned product traits (Coleman and Williams 2013; Reed et al. 2012; Weiss and Johar 2013; Wheeler, DeMarree, and Petty 2007). For example, consumers who wear fake sunglasses

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(presumably feeling ownership of the sunglasses; see Weiss and Johar 2016) are more likely to exhibit fake behavior (i.e., cheat) than those who wear an authentic pair of sunglasses (Gino, Norton, and Ariely 2010). In an academic setting, undergraduate participants who used an MIT pen were likely to perform better on a GRE test than those who used a Pilot pen, and this product-self assimilation was stronger among entity theorists who used the product to bolster their perceptions of their fixed ability (Park and John 2014). Overall, research has convincingly demonstrated that owned product traits transfer to the self, and that consumers exhibit product-congruent behaviors on product-related tasks (McCracken 1986). Such assimilation of the self to owned products can occur through inferential (Park and John 2014) or categorization processes (Weiss and Johar 2013).

While past research has clearly demonstrated behavioral assimilation to the identity activated by an owned product, it has been silent about behaviors related to other identities. The assumption thus far appears to be that performance facilitation as a result of ownership-induced identity activation does not impose any costs on performance related to other identities. Contrary to this view, we suggest that activation of the owned product-identity is likely to result in simultaneous deactivation of product-unrelated identities, resulting in impaired performance on product-unrelated tasks. We base our prediction on research by Bodenhausen et al. (2003) that suggests that people want to behave in a coherent and situationally appropriate manner (Hugenberg and Bodenhausen 2004), resulting in the active inhibition of identities that make the self-view less cohesive when one particular identity is activated (Hugenberg and Bodenhausen 2004; Macrae, Bodenhausen, and Milne 1995; Neill 1977). Among competing representations of identities, people selectively attend to a focal category and the selected target category guides subsequent processing (Bodenhausen 1988; Macrae, Bodenhausen, and Milne 1995; Mercurio

and Forehand 2011). Unattended categories are not passively ignored but are actively suppressed (Neill 1977), because these categories are treated as distractors during information processing (Deutsch and Deutsch 1963).

The idea that individuals have multiple identities and that activation of one can lead to an inhibition of the other has received some empirical support (Bodenhausen, Macrae, and Hugenberg 2003; Macrae, Bodenhausen, and Milne 1995). For example, when Chinese Americans had their Chinese identity activated by seeing the face of another Chinese (vs. Caucasian) person, they suppressed their American identity as indicated by their impaired fluency in English (Zhang et al. 2013). Similarly, Asian American women performed better on a mathematics test when their Asian identity was activated compared to when their gender identity was activated (Shih, Pittinsky, and Ambady 1999; see also Gibson, Losee, and Vitiello 2014; Moon and Roeder 2014).

Activation of one identity leading to deactivation of a different identity may seem relatively intuitive for conflicting identities, where activation of one identity automatically implies suppressing a conflicting identity. This is the case in the two findings cited above. In fact, the Shih et al. (1999) finding may simply reflect behavior that is consistent with the activated stereotype. The literature provides some evidence for deactivation of identities unrelated to the currently active identity, although the findings have not necessarily been interpreted using our theoretical lens (Kettle and Häubl 2011; Macrae, Bodenhausen, and Milne 1995; Winterich and Barone 2011). For instance, when lab participants had their student identity activated (vs. not activated), they were more engaged in an identity-congruent camera shopping task, but less engaged in an identity-unrelated, dishwasher shopping task (Kettle and Häubl 2011). Another study found facilitation on a lexical decision task for words related to the

activated identity but inhibition for words related to a different identity, compared to those who

had no identity activated (Macrae, Bodenhausen, and Milne 1995). These findings are consistent

with research in social cognition that suggests that the activation of a target representation

benefits when inhibitory mechanisms suppress interfering alternatives (Neill 1977).

Figure 1
Theoretical Model
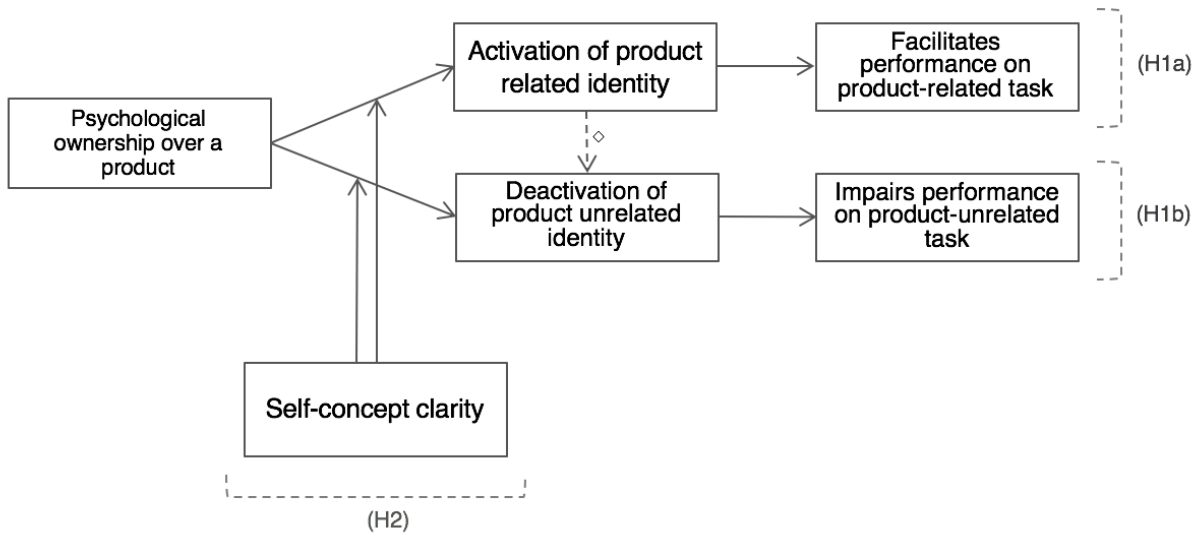
◇ Note – Identity activation and deactivation could be either simultaneous or sequential.

Based on the literature discussed above, we derive the following hypotheses (see

conceptual model in Figure 1).

- o *H1a. Relative to a baseline condition, salience of product ownership facilitates performance on product-related tasks.*

- o *H1b. Relative to a baseline condition, salience of product ownership impairs performance on product-unrelated tasks.*

As discussed above, we invoke the notion of identity activation to justify these hypotheses. An alternative perspective on why feelings of ownership may influence performance on product related and unrelated tasks is that the salience of owned products simply primes product-related goals and deactivates other goals. To tease apart these two potential mechanisms, we turn to the construct of self-concept clarity. Self-concept clarity (SCC) is defined as the extent to which the contents of a person's self-concept are clearly and confidently defined, internally consistent, and temporarily stable (Campbell et al. 1996; Morrison and Wheeler 2010). People with a clear self-concept are more likely to commit to one identity and are less likely to reconsider their self-view on a daily basis (Schwartz et al. 2011). Individuals with high self-concept clarity are less likely to have fluctuating self-views when encountering negative life events (DeHart and Pelham 2007). In contrast, people who have low self-concept clarity hold uncertain, instable, and inconsistent self-views that differ from time to time. If our effects are driven by the activation and deactivation of different aspects of one's identity rather than goal priming, ownership-induced effects on identity and task performance should be attenuated under high self-concept clarity conditions. This is because individuals with high self-concept clarity have stable self concepts and cues such as feelings of product ownership are less likely to activate and deactivate different identities. On the other hand, individuals with low self-concept clarity have less stable self concepts and their self-identities are more likely to be activated by environmental cues such as products and possessions.

> H2: Hypothesis 1 is more likely to hold for individuals who are low on self-concept
> clarity.

Overview of Experiments

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Our theoretical framework posits activation of the self when feelings of product ownership are salient, regardless of whether ownership is psychological (i.e., feelings of ownership) or actual (i.e., legal ownership). Across experiments, we use both types of ownership manipulations. Experiment 1 uses the experimental causal-chain design approach (Spencer, Zanna, and Fong 2005)Experiment 1) to establish the underlying activation process. Experiment 2 uses a well-grounded psychological ownership manipulation to demonstrate attenuated task performance on product-unrelated tasks. Experiment 3 replicates the finding using a different ownership manipulation and measure of performance. Experiment 4 activates two different identities and shows that performance on the exact same task is enhanced when the activated identity is consistent with the task label and attenuated when the identity is inconsistent with the label. Experiment 5 uses the moderation approach to pin down the underlying activation process (H2) and shows that the performance effects are attenuated under high self-concept clarity.

3.2. Experiment 1

Identity (De)Activation during Shopping Task

The goal of Experiment 1 is to test whether shopping for products for oneself activates the product related identity and deactivates other unrelated identities with downstream consequences for performance on product-unrelated tasks. Prior literature in psychology and marketing has activated identities by increasing the salience of products that people already own, using writing and/or recall tasks (Chugani, Irwin, and Redden 2015; Coleman and Williams 2013). To our knowledge, existing research has not yet shown that the mere act of shopping can activate certain identities with consequences for subsequent performance.

By employing an experimental-causal-chain design approach (Spencer, Zanna, and Fong 2005), Experiments 1A-C demonstrate that feelings of product ownership result in identity (de)activation and product-related performance impairment. Specifically, Experiment 1A reveals that shopping for designer IKEA products can activate the art-related identity and simultaneously deactivate art-unrelated identities (the IV → mediator link). Experiment 1B manipulates the extent to which art identity is activated and shows its detrimental effect on a supposedly unrelated shopping task that requires math skills (the mediator → DV link). Lastly, Experiment 1C shows a direct link between the IKEA shopping task and performance impairment on the math-related shopping task (the IV → DV link).

The experimental-causal-chain approach is useful when it is difficult to test the entire conceptual model, with (de)activation as a mediator in the relationship between salience of ownership and task performance in a single study. This is because of the carryover effects resulting from measurement. Activation and task performance need to be measured soon after the ownership salience manipulation and measuring one could influence responses to the other. We therefore test the entire conceptual model by using this approach, showing that if the first link between ownership salience and (de)activation is disrupted (under high self concept clarity), the downstream performance effects do not hold.

Experiment 1A. Shopping for IKEA Designer Products and Art Identity Activation

The goal of Experiment 1A is to test the first link of the conceptual model. We expect that shopping for IKEA products for oneself will lead to an activation of participants' art identity and a deactivation of art-unrelated identities.

Methods

    We used an IKEA catalog shopping task to manipulate ownership and activate an art identity. IKEA is well known for its home décor products inspiring consumers to artistically decorate their living areas, and design their homes. IKEA can therefore be viewed as being linked with an artistic aspect of the self. Ninety-three MTurk participants (44.1% male, M_{age} = 40.07, SD = 12.82) first engaged in an IKEA shopping task where they were randomly assigned to either the ownership or the baseline condition. All participants browsed an online IKEA catalog with three images that showed a list of furniture and other items (see Appendix 1). Depending on their condition, participants were asked to identify five furniture/items that they would like to own (*ownership* condition) or five furniture/items that they thought would be suitable for senior citizen homes (*baseline* condition). All participants then spent at least three minutes to describe why they had chosen the products. The amount of time participants spent on the shopping task across the two conditions did not differ (F < 1).

    In the next ostensibly unrelated task, all participants responded to a "sentence completion task" where they had to fill in 20 sentences beginning with the stem, "I am good at _____." This 20-statement task (Kuhn and McPartland 1954; Weiss and Johar 2016) was used to measure the activation of different identities. Upon completing the sentence completion task, participants were shown their 20 statements and coded whether each statement was related to an art skill set or a non-art related skill set. The proportion of art-related sentences served as our dependent variable.

Results and Discussion

The number of completed statements did not differ between the two conditions ($M_{ownership}$ = 14.42 vs. $M_{baseline}$= 15.49, F < 1). As expected, participants in the ownership condition generated a greater proportion of statements related to art skills ($M_{ownership}$ = 36.02%, SD = .26) than participants in the baseline condition ($M_{baseline}$= 25.52%, SD = .18; $F(1, 91)$ = 5.09, p = .027, d = .45), in response to the 20-statement task.

Additional analysis on the first 3 identities listed in the 20-statement task also revealed a similar pattern of results. Participants in the ownership condition reported a greater number of art-related identities than those in the baseline condition ($M_{ownership}$ = 1.48, SD = 1.14 vs. $M_{baseline}$ = .95, SD = 1.00, $F(1, 92)$ = 5.47, p = .022), further supporting the idea that salience of ownership of art-related products activates art-related identity. Given the fixed number of statements, these findings also serves as evidence for deactivation of non art-related identities.

Two follow-up experiments using different dependent measures (word completion task, cognitive accessibility task) further corroborate these findings and clearly show identity activation of owned product-related identities and deactivation of product-unrelated identities.

Experiment 1B. Activation of Art Identity and Downstream Consequences

Building on the results from Experiment 1A, Experiment 1B tests the downstream consequences of identity activation on product-unrelated task performance. While our conceptualization highlights the role of identity activation, an alternative explanation is that performance effects are goal-driven such that participants simply find the owned product-unrelated task to be irrelevant and consciously disengage from the task. To test this alternative explanation, we measure participants' involvement, effort and perceived task difficulty.

Method

Following the procedure for the experimental causal chain design analysis (Spencer,

Zanna, and Fong 2005), we next manipulated the mediator of art-identity activation using the 20-

statement task from Experiment 1A. Specifically, 95 MTurk participants (47.4% male, M_{age} =

37.18, SD = 12.26) were randomly assigned to either the art identity or the baseline identity

condition. Participants in both conditions responded to the "sentence completion task" where

they completed seven sentences that started with "I am good at ____." The only difference

between the art identity and the baseline identity condition was the instruction where those in the

art identity condition were asked to fill in the blanks with the artistic/designer aspects of the self.

Participants in the baseline condition did not receive this identity-specific instruction. We used a

seven-statement (instead of twenty-statement) task to ensure that participants in both conditions

did not find the sentence completion task too difficult. As expected, particpants in both

conditions were able to complete most of the 7 statements ($M_{art\ identity}$ = 6.81 vs. $M_{baseline\ identity}$ =

6.98 out of 7 statements). After responding to the 7 statements, participants were asked to

indicate the degree to which each of the 7 statements related to art/design skills (1= this skill is

not at all related to one's skills in art and design, 13 = this skill is very much related to one's

skills in art and design). The responses from the 7 statements were averaged and used as the

identity activation manipulation check measure.

All participants then moved on to the ostensibly unrelated "Pantry item shopping" study

where their performance on a math task was measured. They were told that grocery stores carry

products that differ in bundle sizes and prices, and that consumers often have to compare price

per unit to choose bundles with the best deal. A total of 10 pairs of bundled products (e.g.,

toothpaste) were shown and participants were asked to choose the bundled product that had a

lower price per unit (e.g., $6.99 for 3 toothpastes vs. $4.25 for 2 toothpastes; Appendix 2).

Performance was scored in terms of accurately choosing a product bundle among the two bundle

choices (1: correct, 0: incorrect), and the total possible score ranged from 0 to 10. Lastly, all

participants responded to involvement, effort and perceived difficulty questions for the pantry

item task: "How involved were you in the task?"/ "How much effort did you put in the task?"/

"How difficult was the task?" (1: not much involved/ not much effort/ not difficult at all, 7: very

difficult/ very involved/ a lot of effort).

Results and Discussion

Participants' self-reported levels of involvement, effort and perceived difficulty did not

differ between the two conditions (all p's > .127), suggesting that performance differences were

not consciously driven. Participants in both conditions were highly engaged in the pantry item

shopping task (M_{effort} = 6.06; $M_{involvement}$ = 6.00 on a 7-point scale). The task was perceived to be

moderately easy ($M_{difficult}$ = 3.68 on a 7-point scale).

Consistent with our prediction, participants in the art identity condition were less accurate

in choosing products with the lower unit price than those in the baseline condition ($M_{art\ identity}$ =

6.38, SD = 1.92 vs. $M_{baseline\ identity}$ = 7.28, SD = 2.11; $F(1, 93)$ = 4.63, p = .034, d = .45).

Together, experiments 1A-B demonstrate that feelings of ownership (de)activate product-

(un)related identity (Exp 1A) and lead to performance impairment on a product-unrelated task

(Exp 1B).

Experiment 1C. Shopping for IKEA Products and Pantry Shopping Task

Experiment 1C shows a direct link between feelings of ownership and performance impairment, using the IKEA catalogue shopping task as the independent variable and the pantry item shopping task as the dependent variable.

Method

We expected that participants who shopped for their own (vs. senior) home in the IKEA catalogue task would perform worse on the pantry item task that required math skills. MTurk participants ($N = 102$; 44.1% male, $M_{age} = 36.12$, $SD = 11.13$) were randomly assigned to either the ownership or the baseline conditions and completed the identical IKEA manipulation task described in Experiment 1A. They then moved on to the "Pantry item shopping" study identical to that in Experiment 1B, where their performance on a math task was measured. Lastly, all participants responded to involvement, effort and perceived difficulty questions for the pantry item task, identical to those in Experiment 1B.

Results and Discussion

Participants were highly engaged in the pantry item task across conditions ($M_{effort} = 6.11$; $M_{involvement} = 6.00$ on a 7-point scale). The task was perceived to be moderately easy ($M_{difficult} = 3.52$ on a 7-point scale). Participants' self-reported levels of involvement, effort and perceived difficulty did not differ between conditions (all p's > .294).

Task performance. Consistent with our prediction, participants in the ownership condition were less accurate in choosing products with the lower unit price than those in the baseline condition ($M_{ownership} = 6.58$, $SD = 1.84$ vs. $M_{baseline} = 7.58$, $SD = 1.82$; $F(1, 100) = 7.57$, $p = .007$, $d = .55$).

Supporting prior findings that identity-driven performance is not consciously goal-driven (Shih, Pittinsky, and Ambady 1999), we did not find any differences in involvement, effort and perceived difficulty across the ownership and the baseline condition. To further rule out the goal explanation which would hold that post-IKEA shopping performance is driven by participants in the ownership condition having the goal to do well on art-related tasks but not on other tasks (such as pantry item math task), we conducted a follow-up experiment (N = 126; 45.7% male, M_{age} = 34.65, SD = 8.19). This experiment employed the same IKEA ownership manipulation, pantry item shopping task, and 4 items that measured participants' goals on art- and math related tasks: (1) It is important for me to do well in art/design-related tasks, (2) I want to be good at design/art related tasks, (3) It is important for me to do well in math-related tasks, (4) I want to be good at math related tasks (1: not true at all, 7: totally true). We again replicated the main findings that feelings of ownership over IKEA products leads to worse performance on the pantry item math task ($M_{ownership}$ = 6.07, SD = 1.90 vs. $M_{baseline}$ = 6.76, SD = 1.93, F(1, 124) = 4.08, p = .046, d = .36). The 4 goal measures (2 items for art, 2 items for math) were respectively averaged to compose the art-goal activation and math-goal activation scores. These scores did not differ across the two conditions (art-goal activation: $M_{ownership}$ = 4.73 vs. $M_{baseline}$ = 4.76; F < 1; math-goal activation: $M_{ownership}$ = 4.64 vs. $M_{baseline}$ = 4.43; F < 1).

Overall, results from experiments 1A-C suggest that shopping for a product activates product-related identities and deactivates product-unrelated identities. In support of H1(b), we also demonstrate the downstream consequences of such deactivation; participants who shopped the IKEA catalog for their own homes performed worse on a subsequent pantry shopping task that required math skills. Additional support of identity (de)activation upon product ownership also comes from follow-up experiments I - III that utilized different ownership manipulations

and different cognitive accessibility tasks to measure activation. The details of these experiments can be found in Appendix 3.

In the next set of experiments, we manipulate ownership in different ways and systematically explore downstream consequences of activation and deactivation using a full 2 (ownership: yes vs. no) × 2 (quiz label relevance: product-related vs. product-unrelated) between-subjects experimental design. By using the same task, but framing it as either product-related vs. unrelated, we can rule out any role for task content and pin down the role of identity (de)activation.

3.3. Experiment 2

Psychological Ownership of a Calculator and Performance on Math vs. Creative Writing Labeled Tasks

The goal of Experiment 2 is to examine the consequences of activating one identity on task performance on product-related and product-unrelated tasks. We used a validated psychological ownership manipulation (Peck and Shu 2009), and measured performance on an anagram task labeled as either product-related or unrelated.

Method

One hundred-eighty-seven MTurk participants (36.4% male, $M_{age} = 35.87$, SD = 12.51) were randomly assigned to one of the 4 conditions in a 2 (psychological ownership: ownership vs. baseline) × 2 (quiz label relevance: related vs. unrelated) between-subjects design. First, participants completed an ownership manipulation where they saw an image of a calculator and either imagined bringing the calculator home (*ownership* condition) or described which store

would carry the calculator (*baseline* condition). In the next ostensibly unrelated study, participants were informed that the task would measure their math skills (vs. creative writing skills) by testing how well they recognize meaningful words from scrambled letters. The framing of the quiz – math vs. creative writing – was chosen based on our pretest showing that the two skills are perceived to be unrelated to each other. Subsequently, all participants responded to a 10-item anagram quiz that was labeled as measuring individuals' math skills (calculator *product-related label* condition) or creative writing skills (calculator *product-unrelated label* condition). In fact, both quizzes were composed of identical anagram questions (e.g., solutions were 'power', 'matrix', 'slope') that could plausibly be perceived as a test of math or creative writing skills. Finally, all participants responded to demographic and debriefing questions.

Figure 2
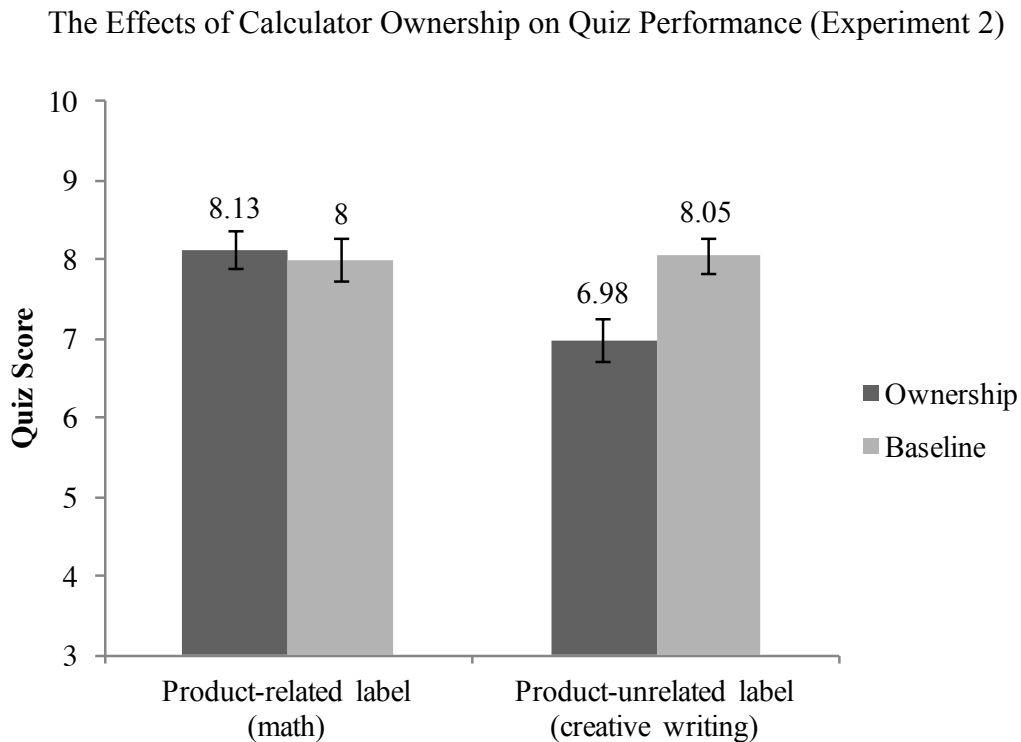
The Effects of Calculator Ownership on Quiz Performance (Experiment 2)

NOTE.— Mean quiz score on the task labeled as product-unrelated was significantly lower in the ownership vs. baseline condition.

Results and Discussion

Participants were highly engaged in the task across conditions (M_{effort} = 5.96; $M_{involvement}$ = 6.55 on a 7-point scale). The task was perceived to be moderately easy ($M_{difficult}$ =3.93 on a 7-point scale). Participants' self-reported levels of involvement, effort and perceived difficulty did not differ between conditions (all p's > .148), suggesting that any uncovered performance differences were not consciously driven (Shih, Pittinsky, and Ambady 1999).

A 2 × 2 between-subjects ANOVA revealed a marginal main effect of psychological ownership ($F(1, 183)$ = 3.35, p = .069), such that participants in the calculator ownership condition generally scored lower than those in the baseline condition. A main effect of quiz label ($F(1, 183)$ = 4.51, p = .035) revealed that participants in the creative writing label condition scored lower than those in the math label condition. These effects were qualified by a significant interaction between ownership and quiz label relevance ($F(1, 183)$ = 5.35, p = .022). Consistent with the deactivation account, participants in the calculator ownership condition performed worse than those in the baseline condition on the quiz labeled as a creative writing task ($M_{ownership, creative writing label}$ = 6.98, SD = 2.00 vs. $M_{baseline, creative writing label}$ = 8.05, SD = 1.40; $F(1, 183)$ = 7.96, p = .006, d = .62). We did not observe a significant activation effect within the math-quiz label condition ($M_{ownership, math label}$ = 8.13, SD = 1.67 vs. $M_{baseline, math label}$ = 8.00, SD = 1.85; $F < 1$); this could be due to a ceiling effect resulting from high scores (> or = 8 out of 10) in both conditions. The quiz scores within the ownership condition were also significantly different from each other ($M_{ownership, creative writing label}$ = 6.98, SD = 2.00 vs. $M_{ownership, math label}$ = 8.13, SD = 1.67; $F(1, 183)$ = 10.38, p = .002, d = .64). There were no significant differences

within the baseline condition ($M_{\text{baseline, creative writing label}}$ = 8.05, SD = 1.40 vs. $M_{\text{baseline, math label}}$ = 8.00, SD = 1.85; F < 1).

Results from Experiment 2 demonstrate that participants who feel ownership over a calculator perform worse on a creative writing labeled quiz that is unrelated with one's activated math identity (H1b). Evidence for deactivation comes from the comparison of scores in the calculator ownership vs. baseline condition within the creative writing quiz, as well as from comparing scores on the quiz labeled as math vs. creative writing within the ownership condition. We do not observe evidence for activation on the math labeled quiz in the ownership vs. baseline condition (H1a) – scores are uniformly high in both conditions and we speculate that this is because of a ceiling on possible scores on this easy quiz.

3.4. Experiment 3

Ownership of a Calculator and Performance on Math vs. Visual Sensitivity Labeled Quiz

Experiment 3 demonstrates the robustness of the performance effects by using a legal (rather than psychological) ownership manipulation and a moderately difficult performance task to prevent ceiling effects.

Method

One-hundred four Mturk participants (44.2% male, M_{age} = 35.04, SD = 11.57) were randomly assigned to one of the four conditions in a 2 (ownership: ownership vs. baseline) × 2 (quiz label relevance: related vs. unrelated) between-subjects design. All participants first engaged in a "computer software" study where they were assigned to either the calculator ownership or the baseline condition. In both conditions, participants were asked to spend at least

3 minutes to describe how they would locate a calculator program on a computer desktop. The only difference between the two conditions was that participants either described the location of the calculator program on their personal computer (*ownership* condition), or on a typical public library computer (*baseline* condition). Next, participants completed an ostensibly unrelated second study. The cover story described the task as measuring the variance in people's ability to perform math (vs. visual sensitivity) tasks. Participants were randomly assigned to solve either a math labeled quiz (*product-related label* condition) or a visual sensitivity labeled quiz (*product-unrelated label* condition), the labels of which were chosen based on a pretest. Both the quizzes were composed of ten identical questions. For example, participants saw five boxes that were filled with different arithmetic signs (+, ?, ×, =) and predicted the composition of the arithmetic signs inside the 6th box (see Appendix 4). Next, participants responded to three questions measuring their levels of involvement and effort, and the perceived difficulty of the quiz. Finally, all participants reported whether they used a PC or Mac, the frequency of using the calculator program, and their demographics.

Results and Discussion

Ratings of how interesting the manipulation task was did not differ between conditions ($F < 1$), casting doubt on a potential alternative account that participants in the public computer (vs. my computer) condition were demotivated. Further, participants' self-reported level of involvement, effort and perceived difficulty in the quiz did not significantly differ across conditions suggesting that any observed performance effect was not conscious. Moreover, the level of effort and involvement in the quiz was high in all four conditions ($M_{effort} = 6.03$; $M_{involvement} = 6.18$ on a 7-point scale), suggesting that participants across all conditions were

highly engaged in taking the quiz. The quiz was perceived as difficult ($M_{difficult}$ =5.72 on a 7-point scale).

Figure 3

The Effects of Calculator Ownership on Quiz Performance (Experiment 3)
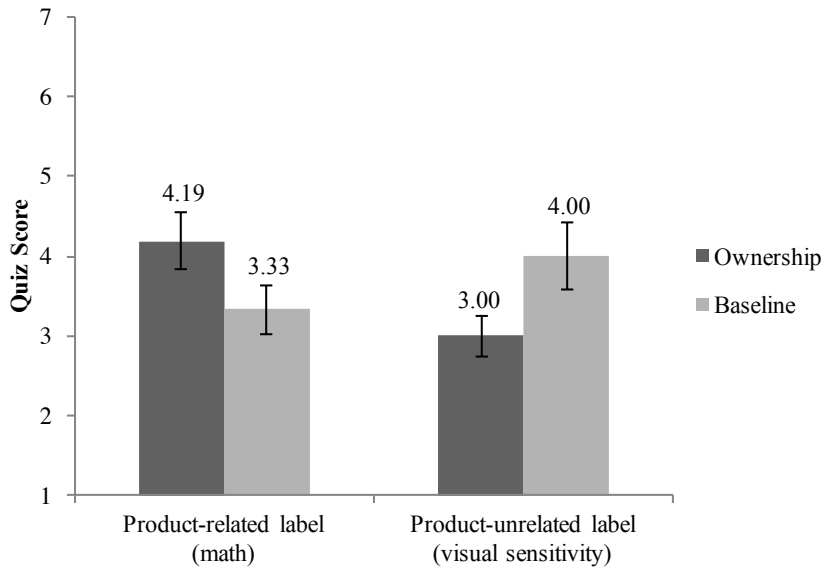
NOTE.— Mean quiz score on the task labeled as product-related was significantly higher in the ownership vs. baseline condition. Mean quiz score on the task labeled as product-unrelated was significantly lower in the ownership vs. baseline condition. The means within the baseline condition were not significantly different from each other.

Quiz performance. The 2 × 2 between-subjects ANOVA revealed only a significant interaction of ownership × quiz label ($F(1, 100) = 7.50$, $p = .001$). In support of the deactivation hypothesis (H1b), when the quiz was labeled as a visual sensitivity quiz, participants in the calculator ownership condition performed worse than those in the baseline condition ($M_{ownership,\ visual\ sensitivity\ label} = 3.00$, SD = 1.46 vs. $M_{baseline,\ visual\ sensitivity\ label} = 4.00$, SD = 2.02, $F(1, 100) = 7.50$, $p = .038$, d = .58). In support of the activation hypothesis (H1a), when the quiz was labeled as a math quiz, participants in the calculator ownership condition performed marginally better

than those in the baseline condition ($M_{ownership, math label}$ = 4.19, SD = 1.66 vs. $M_{baseline, math label}$ = 3.33, SD = 1.71; $F(1, 100) = 3.13$, $p = .080$, d = .50). Additional analysis revealed that, participants in the calculator ownership condition performed significantly worse on the visual sensitivity labeled quiz than on the math labeled quiz ($M_{ownership, visual sensitivity label}$ = 3.00 vs. $M_{ownership, math label}$ = 4.19; $F(1, 100) = 6.12$, $p = .015$, d = .77). However, participants' scores did not differ in the baseline conditions ($M_{baseline, visual sensitivity label}$ = 4.00 vs. $M_{baseline, math label}$ = 3.33; $F(1, 100) = 1.95$, $p = .166$, d = .36). Participants' ownership of PC/Mac did not differ significantly between conditions and the frequency of using a calculator did not moderate the effects in any way.

Experiment 3 replicated the deactivation findings (H1b) and provided marginal support for activation as a result of ownership (H1a). Similar to Experiments 1 and 2, additional analysis on participants' involvement and perceived quiz difficulty revealed no differences across conditions. Overall, results from Experiments 1 to 3 converge to show that salience of ownership over a product activates product-related selves and deactivates product-unrelated selves. The deactivation of a product-unrelated self resulted in impaired performance on a task labeled as product-unrelated. Experiment 4 replicates these performance effects by activating two different identities between subjects and showing evidence for comparative activation and deactivation.

3.5. Experiment 4
Shifting Identity and Task Performance on Matched vs. Mis-matched Tasks

The goal of Experiment 4 is to activate different identities across participants and show evidence for enhanced performance when the task label matches the activated identity and impaired performance when the task label mismatches the activated identity. To test this idea, we

use two different ownership conditions rather than a baseline condition. Thus, a matching label in one condition is a mismatching label in the other condition. Once again, the performance task is exactly the same in all conditions.

Method

One hundred-seventy-four behavioral lab participants (31.6% male, M_{age} = 23.17, SD = 5.11) at a large Northeastern university participated in the experiment. Participants were randomly assigned to one of the four conditions in a 2 (ownership: scientific calculator vs. art piece) × 2 (quiz label relevance: math vs. artistic sensitivity) between-subjects design. Participants first responded to the "marketing and product usage" survey where they spent at least 3 minutes describing a scientific calculator (vs. art piece) that they owned. We chose these products because most undergraduate students are required to own a scientific calculator for their core math classes and most students own art pieces (e.g., posters, sculpture, art frames) in their dorms.

Next, participants engaged in an unrelated second study that stated that the researchers were interested in measuring their math or artistic sensitivity skills. The quiz content was identical to that in Experiment 3 in both conditions. Note that the quiz uses mathematical symbols in boxes and can plausibly be perceived as a math or artistic sensitivity quiz (Appendix 4). Finally, participants reported their levels of effort and involvement in the quiz and the perceived quiz difficulty. This was followed by some demographic and debriefing questions.

Results and Discussion

Participants' self-reported levels of effort and involvement and the perceived difficulty of the two quizzes did not differ across conditions. Participants across all conditions were generally engaged in the quiz (M_{effort} = 4.99; $M_{involvement}$ = 5.33 on a 7-point scale), and perceived the quiz to be somewhat difficult ($M_{difficult}$ = 5.18 on a 7-point scale).

Figure 4

Shifting Self Identities and Task Performance (Experiment 4)
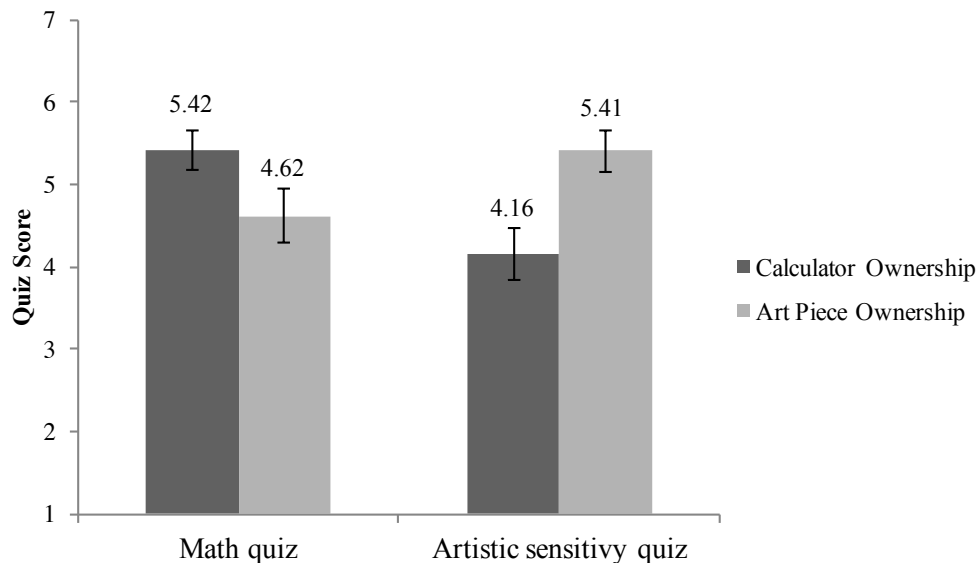
NOTE.— Mean math labeled quiz performance was higher in the calculator ownership condition compared to the art piece ownership condition. Mean artistic sensitivity labeled quiz performance was higher in the art piece ownership condition compared to the calculator ownership condition.

Quiz performance. The 2 × 2 between-subjects ANOVA revealed only a significant ownership × quiz label interaction ($F(1, 170)$ = 13.17, $p < .001$). As expected, among those who solved an artistic sensitivity labeled quiz, participants in the calculator ownership condition performed worse than those in the art piece ownership condition ($M_{calculator, artistic\ sensitivity\ label}$ =

4.16, SD = 2.02 vs. $M_{\text{art piece, artistic sensitivity label}}$ = 5.41, SD = 1.72; $F(1, 170) = 10.02$, $p = .002$, d

= .67). In contrast, among participants who solved a math labeled quiz, those in the calculator

ownership condition performed better than those in the art piece ownership condition ($M_{\text{calculator,}}$

$_{\text{math label}}$ = 5.42, SD = 1.59 vs. $M_{\text{art piece, math label}}$ = 4.62, SD = 2.08; $F(1, 170) = 3.92$, $p = .049$, d

= .43). Additional analysis revealed that participants in the art piece ownership condition

performed worse on a math labeled quiz than on an artistic sensitivity labeled quiz ($M_{\text{art piece, math}}$

$_{\text{label}}$ = 4.62, SD = 2.08 vs. $M_{\text{art piece, artistic sensitivity label}}$ = 5.41, SD = 1.72; $F(1, 170) = 3.99$, $p = .047$,

d = .41). On the other hand, participants in the scientific calculator ownership condition

performed worse on an artistic sensitivity labeled quiz than on a math labeled quiz ($M_{\text{calculator, math}}$

$_{\text{label}}$ = 5.42, SD = 1.59 vs. $M_{\text{calculator, artistic sensitivity label}}$ = 4.16, SD = 2.02; $F(1, 170) = 9.78$, $p = .002$,

d = .69).

Results from Experiment 4 provide convincing evidence of both relative performance

enhancement (H1a) and relative performance impairment (H1b) by activating either the art or the

math identity. If, as we contend, activation of different identities is the mechanism underlying

the effects of ownership on task performance, then the effects should be stronger for those with

low self-concept clarity whose identities are more malleable and change based on social cues and

environmental influence (Campbell et al. 1996). We test this idea in the following experiment.

3.6. Experiment 5

Self Concept Clarity Moderates the Effect of Ownership on Task Performance

We provide evidence for the underlying mechanism of identity activation by using self-

concept clarity as a moderator.

Method

A total of 383 Mturk participants were randomly assigned to one of the eight conditions in a 2 (self-concept clarity: high vs. low) × 2 (psychological ownership: ownership vs. baseline) × 2 (quiz label relevance: product-related vs. product-unrelated) design. First, self-concept clarity was manipulated by asking participants to recall a past incident where they had (vs. did not have) a clear and a consistent sense of the self (Rozenkrants, Wheeler, and Shiv 2017). After the writing task, participants were led to an ostensibly unrelated second study where they responded to the calculator ownership manipulation task used in Experiment 2 (Peck and Shu 2009). Finally, participants responded to the same performance task as in Experiments 3 and 4; the task was either framed as measuring their math skills (calculator *product-related label* condition) or their artistic skills (calculator *product-unrelated label* condition).

Results and Discussion

Similar to results from prior experiments, there were no significant differences in participants' self-reported levels of involvement, effort and perceived difficulty. Participants were generally engaged (M_{effort} = 6.01, $M_{involvement}$ = 6.22 on a 7-point scale). The quiz was perceived as difficult ($M_{difficult}$ = 5.89 on a 7-point scale).

Quiz performance. There was a significant 3-way interaction between self-concept clarity, ownership and quiz label ($F(1, 375)$ = 5.84, p = .016), as well as a marginally significant 2-way interaction between ownership and quiz label ($F(1, 375)$ = 3.21, p = .074). Consistent with our prediction, there was a significant 2-way interaction of ownership × quiz label within the low self-concept clarity condition ($F(1, 375)$ = 7.92, p = .005), but not within the high self-concept

clarity condition (F < 1). Within the low self-concept clarity condition, we found support for

both deactivation (H1b: $M_{ownership, art\ label}$ = 2.81, SD = 1.30, $M_{baseline, art\ label}$ = 3.65, SD = 1.87, F(1,

375) = 5.08, p = .025, d = .53), as well as activation (H1a: $M_{ownership, math\ label}$ = 3.74, SD = 1.87,

$M_{baseline, math\ label}$ = 3.04, SD = 1.67, F(1, 375) = 3.79, p = .052, d = .39; see).

Within the ownership condition in the low self-concept clarity condition, participants

performed significantly worse on an art task than on a math task ($M_{ownership, math\ label}$ = 3.74 vs. M

$_{ownership, art\ label}$ = 2.81, F(1, 375) = 7.16, p = .008, d = .58). There was no significant performance

difference within the baseline condition (F(1, 375) = 2.53, p = .11, d = .34).

In an additional study, we measured (vs. manipulated) individual differences in self-

concept clarity and replicated the results of Experiment 5. See the Follow-up Experiment in

Appendix 5 for details.

Figure 5

Figure 5A. Low Self Concept Clarity (SCC) Condition (Experiment 5)
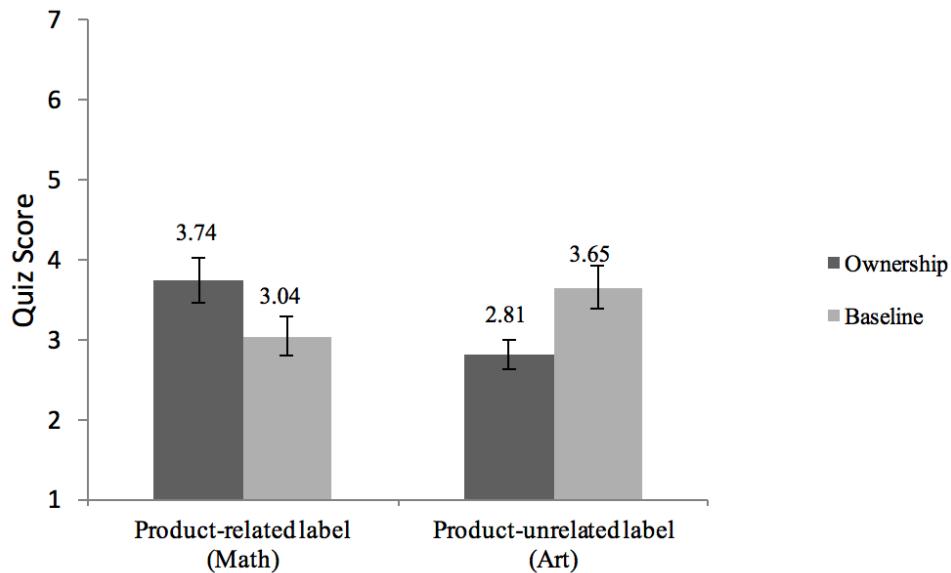
Figure 5B. High Self Concept Clarity Condition (Experiment 5)
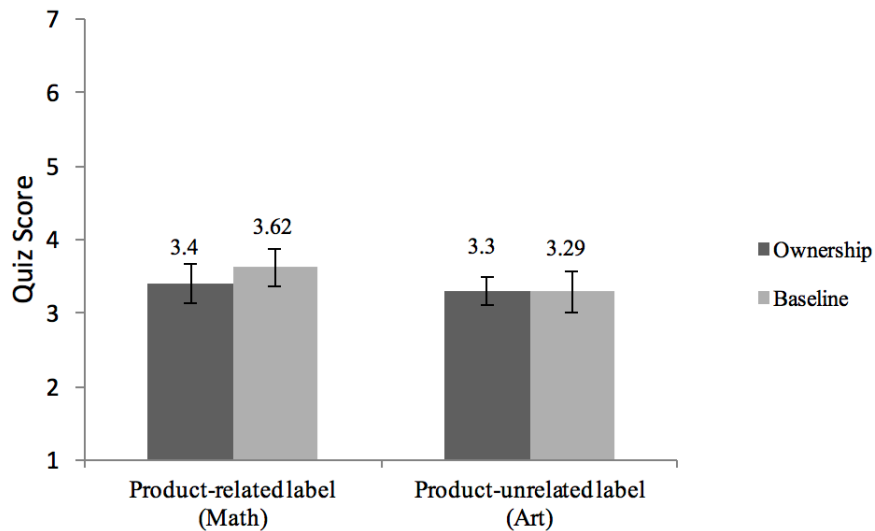
NOTE.— Among participants with low SCC, mean quiz score on the task labeled as product-related was significantly higher in the ownership vs. baseline condition. Mean quiz score on the task labeled as product-unrelated was significantly lower in the ownership vs. baseline condition. There was no difference among participants with high SCC.

3.7. General Discussion

Across five experiments, we replicate the finding that the salience of actual or psychological ownership over a product results in performance impairment on product-unrelated tasks. Our explanation for this effect is that salient possessions activate related aspects of the self and deactivate other aspects of the self. This performance difference does not appear to be motivated by a desire to do better on relevant tasks given that self-reported levels of effort and involvement do not differ across conditions. By keeping the task constant and varying only the label, we also rule out inherent task properties as explanations for the effect. Finally, the finding that performance impairment for owned product-unrelated tasks occurs only under low self-concept clarity supports the argument that identity (de)activation stemming from product ownership salience underlies the effect. Under high self-concept clarity, the self concept is not

malleable and salience of product ownership does not result in (de)activation of specific aspects of the self.

We conducted a meta-analysis of all main experiments reported in the paper (McShane and Böckenholt 2017)("Papers on Meta-Analysis | Comprehensive Meta-Analysis" n.d.). Results confirmed a significant impairment effect (H1b; Estimate = -1.06, CI = [0.32, 1.02]). Although the facilitation effect did not obtain at conventional levels of significance in all experiments, results of the meta-analysis reveal a significant facilitation effect (H1a: Estimate = 0.67, CI = [-1.35, -.76]).

Implications

Several important takeaways from our studies deserve to be highlighted. First, innocuous everyday tasks such as shopping can activate and deactivate product-related and unrelated identities with downstream consequences for consumer behavior. Second, activation of aspects of the self can result in deactivation of negatively correlated as well as unrelated aspects of the self. These findings bolster our contention that conscious inferences about the relationship between abilities in each task domain are not necessary for the effects to obtain. Third, sheer priming of the product (as in the baseline conditions) does not produce the same results as feelings of ownership, suggesting that identity activation is driven by possessions that are viewed as being a part of the self.

Theoretical implications. An overarching question concerns whether the performance effects we observe are motivational or cognitive in nature. The motivational explanation would suggest that participants are not motivated to perform well on a task that is associated with the deactivated identity, whereas the cognitive account would suggest that participants

unconsciously disengaged from tasks associated with a deactivated identity. Previous research suggests that both routes are possible. Evidence for the motivational route comes from research showing that exposure to a brand may automatically prime goals and motivate goal-directed behaviors (Fitzsimons, Chartrand, and Fitzsimons 2008). While we construe our findings in terms of activation of different aspects of the self-concept, the underlying part-of-self mechanism could also be viewed as conferring commitment to a particular identity. Such commitment may not be captured in our measures of goal importance and engagement. Teasing apart the role of activation from that of commitment awaits further investigation.

Having a clear self-concept is one way to prevent the negative performance effect of possessions. One may question whether individuals who have multiple identities are more likely to be susceptible to these influences. Unlike this intuition, people with multiple identities have high self-complexity (Linville 1987), and these individuals are more successful at shifting between different identities under threat (Linville 1985). Therefore it is possible that people with high self-concept complexity are better at avoiding negative effects of possessions. Then what could be some ways to enhance self-concept clarity? Research suggest that self-concept clarity is inter-wined with healthy identity development (Campbell et al. 1996; Crocetti and Dijk 2016), and parents' self-concept clarity has positive effects on children's self-concept clarity. Parents that show acceptance to ideas and viewpoints encourage children to build confidence and explore their own selves (Crocetti and Dijk 2016) and building a healthy communication can promote children's self-understanding (Grotevant and Cooper 1985).

Practical implications. The finding that frequent activities such as shopping can activate product-related identities with downstream consequences for consumer behavior is a clear practical insight of this research. These downstream consequences include impaired performance

on tasks such as price comparisons when non-math related identities are activated during a shopping task. In Experiment 1, shopping for IKEA products for oneself (vs. someone else) activated participants' art identities and deactivated their math identities, resulting in poorer ability to identify good bargains. These results highlight purchase occasions when consumers may be less price sensitive or have lower ability to discern good deals. This finding has implications managers making pricing and promotion decisions in online shopping environments where prices can be manipulated in real-time and consumers' immediate prior online activities are known. We also believe awareness of this effect is important to consumers in order to guard against this tendency.

Task performance on cognitive tasks such as those used in this paper is a variable of critical interest in educational settings. Our findings have implications for the design of academic schedules as well as construction of courses. To maximize learning, it is important that courses that require similar skills be grouped closer so that an appropriate identity is activated and maintained, and that identity switching is minimalized. Design of online courses is particularly key because only a small percentage of enrolled students complete free online courses such as MOOC's ("MOOC Research - What We Know So Far" 2017). One factor that has been found to increase engagement with these courses is to ensure that participants are appropriately challenged (from interviews; Appendix 6). Research has shown that it is possible to increase long-term engagement and achievement in online courses by using a 10-minute writing exercises to reduce social identity threat (Kizilcec et al. 2017). Kizilcec et al (2017) conducted two large field experiments in an online MOOC setting and showed that learners with threatened self-identity in developing countries become more persistent and are more likely to complete a course upon self-affirmation. In a similar manner, online courses can activate course-related identities

so as to maximize engagement and learning. For example, activating a related identity (e.g., a traveler identity) prior to taking a course (e.g., Italian class) could be an effective way to enhance engagement and performance. For underperformers, educators can explore ways to help consumers deactivate undesired identities and adopt a desired identity.

Another industry that could use the insights from our studies is gaming. We interviewed managers at many gaming companies and learned that designing games with the right balance between achievement and challenge is critical to retaining gamers. Identity activation could be one way to achieve such a balance. For example, relevant identities can be activated to improve performance but also deactivated to maintain challenge. While subtle cues such as avatars in a game could be used for identity activation (Kim, Chen, and Zhang 2016), participants could also be taught to adopt the identity needed to excel on each task (e.g., changing avatars depending on the upcoming task). Gamers who perform better are more likely to purchase in-game items and upgrade to paid, premium products. Helping these gamers adopt an identity (e.g., architect identity for Sim City) to increase the sales of related products (e.g., other Sim products, such as Sim Park, Sim Safari) could be a useful marketing tactic. Similarly, different avatars and in-game purchases can be used to facilitate game performance and loyalty.

An interesting implication is to consider a situation where an identity is activated before a goal-driven task. For example, listening to a favorite band music can impair one's performance in an upcoming English test, because the music activates the music-related identity (e.g., being a fan) in his/her mind. Perhaps, this would have a detrimental effect on the test compared to when s/he listens to a neutral music.

Future research. Certain aspects of our paradigm merit discussion and future research. First, we focus on a basic level skill (such as math identity) using ownership of product

categories (e.g., a calculator) to activate these identities. An obvious question concerns the level at which identities are activated—is there a math self or a more general analytical self? We do not take a strong position regarding the hierarchies in which identities reside but suggest that future research examine this issue. Second, the experiments reported in this paper use rather mundane products. It is likely that products and brands that have strong associations are likely to have even larger effects. Third, our follow-up investigation suggests that identity deactivation is more pronounced among identity pairs that are negatively related or unrelated, but not among pairs that are positively related (Appendix 7). Future research can investigate this idea further. Fourth, not only the tangible goods but also experiences (such as being in a favorite concert), emphasis on membership or roles (as opposed to a skillset) can also be used to activate an identity. In sum, possessions can have profound implications for consumer behavior. Our findings open up exciting areas for future research on the impact of possessions on the self.

CHAPTER 4

ESSAY 2: THE SHARING ECONOMY

ABSTRACT

The consumer behavior literature has examined the antecedents and consequences of consumer motivation using experimental research paradigms to shed light on many theoretical facets of motivation. While some of these findings can be applied to consumer welfare, this research has not inspired much application by practitioners. This could be due to the difficulty in uncovering motivations for a large consumer segment and examining the motivations' impact on firms. The present research puts forth a practical technique by which firms can extract consumer motivations from open-ended text responses. Specifically, we extract motivations from 25,290 hosts who list properties on the Airbnb platform by mining their text responses to the question, "why did you start hosting?". We find that Airbnb hosts are driven by three principle motivations – the motivation "to earn cash," "to share beauty," and "to meet people." We find that each of these motivations have unique downstream consequences for hosts' engagement and likelihood of staying on the platform. We use different analytical tools including machine learning and natural language processing, "buy-till-you-die" latent attrition model, and lab experiments. These findings suggest that firms can leverage these motivations to attract the right "type" of customer, which could also dictate firm revenue. (199 words)

4.1. Introduction

Motivation is fundamental to the study of consumer behavior. Scholars have made great strides in understanding the theoretical underpinnings of motivation and self-regulation as well as their consequences. However, research has yet to make a strong case for the examination of customer motivations by practitioners. There are several reasons for the gap between the emphasis on motivation research in the academic literature, and its limited usage in practice. First, it is not clear that the study of customer motivations is relevant to firm decisions because the effect of motivations has mostly been established in the short term, usually with consequences measured in the same lab setting as the manipulation or measurement of motivations (Herbst et al. 2012; Poynor and Haws 2009). Most field studies have focused on the effects of broad categories of motivations such as entity versus incremental mindsets[1] (Blackwell et al 2007) or intrinsic versus extrinsic motivation (e.g., Ashraf, Bandiera and Jack 2014; Grant and Berry 2011). The long-term effect of motivations in complex business contexts have yet to be examined. Second, motivations have often been measured or manipulated in lab settings (Dommer, Swaminathan, and Ahluwalia 2013; Soman and Cheema 2004); however, measuring consumer motivations at an individual level using closed-ended survey questions is not viable at large sample sizes for most firms, and may also not yield reliable and valid results. Third, researchers often manipulate or measure one motivation at a time (Hong and Lee 2008), or examine motivational constructs at an abstract level, whereas multiple concrete motivations are likely to exist and operate together in practice. Given the lack of empirical support for the

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[1] Entity versus incremental theory examines how people develop beliefs about themselves. People with entity mindset treats their internal traits as fixed and stable, while those with incremental mindset views their traits as malleable, fluid and changeable with opportunities for growth (Dweck, Chiu, and Hong 1995)

relationship between customer motivations and firm-level outcomes, there has been little effort by firms to systematically measure and leverage consumer motivations at a granular level to improve long-term consumer-firm relationships.

The objective of this research is to highlight the role that customer motivations play in determining firm-level outcomes. To do so, we provide a practical way for firms to extract latent consumer motivations from textual data and showcase the downstream consequences of these motivations on customer engagement and retention, as well as pricing decisions. Specifically, we uncover motivations from a text dataset obtained from Airbnb, that contains responses of over 43,000 hosts who responded to an open-ended question regarding their motivations to host. The open-ended survey question is analyzed using both multi-label classification and Poisson Factorization to identify hosts' motivations to share their properties. We then examine the downstream behavioral consequences of different types of motivations using the two-year transaction history of these hosts. Specifically, we explore differences in host engagement and hosts' decision to churn using a "buy-till-you-die" model (Fader, Hardie, and Shang 2010). We also examine hosts' pricing decisions as a function of their motivations.

To foreshadow our results, we find that Airbnb hosts are mainly driven by three motivations that may operate singly or jointly: 1) the motivation to earn cash, 2) the motivation to share the beauty of their property, and 3) the motivation to meet people. While the monetary motivation is commonly thought of as the main driver to participate in the sharing economy, we find that nearly 42% of hosts are driven by non-monetary motivations. In contrast to the common intuition that cash-driven hosts are likely to be highly engaged, we find that those who are motivated to share the beauty of their home or to meet people are more likely to stay engaged as shown by their decision to open more nights on their reservation calendar. Moreover, these hosts

are more likely to continue hosting (i.e., less likely to churn from Airbnb). They are also likely to receive more frequent bookings and more positive guest ratings.

Airbnb hosts' pricing decisions also differ by motivations. Hosts who are motivated to share beauty charged the highest, and hosts motivated to meet people charged the lowest prices. Hosts who are motivated to earn cash priced their home in between these two groups. These pricing patterns hold even after controlling for property types and amenities.

Our research makes several contributions. From a substantive point of view, this is one of the first papers to explore the downstream consequences of different motivations extracted from textual data for customer behaviors such as engagement, retention and pricing decisions. Second, we contribute to the growing literature on the sharing economy by using rich secondary datasets from Airbnb and by focusing on host behavior (as supposed to guest behavior), thereby revealing consumers' new role as micro entrepreneurs. Third, from a methodological point of view, we use state-of-the-art machine learning and natural language processing (NLP) approaches to extract motivations from textual responses. These approaches overcome the limitations of numeric-based scale methods and allow firms to identify consumer motivations at a large scale. Importantly, the inductive method to identify consumer motivations helps bridge the quantitative methods and the consumer behavior research in marketing.

In the rest of this paper, we first discuss the limitations of commonly used experimental paradigms in motivation research that make it difficult to adapt these approaches to the field. Next, we provide a brief background of the emerging sharing economy platform and describe our Airbnb dataset. We then adopt multi-label classification and Poisson Factorization approaches to extract and validate motivations from hosts' textual responses. After identifying latent motivations, we explore the relationship between hosts' motivations and their engagement on the

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platform, their retention propensities and their pricing decisions. We do so using several approaches, including model-free evidence, a "buy-till-you-die" model, regression analyses and lab experiment on pricing decision. We conclude with a discussion of the theoretical and managerial implication of our findings.

Motivation Research in Consumer Behavior

Most motivation research in psychology and marketing follows a common experimental paradigm. The experimental paradigm involves manipulating different types of motivations such as promotion- and prevention-focused motivations (Higgins 1998). Some commonly utilized motivation manipulations include a writing task (Dommer, Swaminathan, and Ahluwalia 2013), articles/scenarios reading task (Soman and Cheema 2004), or instructing participants to engage in a certain behavior (e.g., enter a lottery to have their materialism-related motivation activated; Kim 2013). Researchers also measure, as supposed to manipulate, individual differences using pre-defined scales. Scales have often been pre-tested for their reliability in capturing specific motivations, such as the scale to measure avoidance-approach motivation (Elliot and McGregor 2001) or the motivation for social relationship (Dzhogleva and Poynor Lamberton 2014).

While manipulations and measurement of motivation are useful in theoretical research aimed at understanding the antecedents and consequences of different types of motivations, they have limited use in field settings. First, many of the manipulations in experimental settings (e.g., a writing task) can generate a momentary shift in respondents' motivations but cannot be routinely used by marketers. In terms of numeric scale measurement, firms often have difficulty asking a large set of consumers to respond to a set of long and obtrusive motivation scales. Using such scales also requires a-priori knowledge of the motivations that researchers wish to explore.

In emerging domains where new motivations may arise as a result of new modes of marketplace exchange (such as the sharing economy), validated numeric scales may not exist.

A second limitation of motivation-related lab research is the difficulty of exploring long-term effects of motivations. Because manipulations are often short-lived, dependent variables are often bound to short-term perceptual and behavioral responses. Long-term behavioral consequences of motivations have been investigated only to a limited extent because of the high monetary cost as well as the time-consuming nature of such an experimental procedure (Bauer 2004). Some notable exceptions include field experiments such as the study on how incentives affect the motivation to purchase coffee over a period of six weeks (Kivetz, Urminsky, and Zheng 2006), or consumers' status motivation in relation to their enrollment in a loyalty program (Dreze and Nunes, 2009).

To address the first challenge of identifying consumer motivations that are unique to each firm, we propose that marketers collect and analyze consumers' open-ended textual responses. Given the emergence of new communication windows available on the web – whether it be survey responses, review websites, or blogs – consumers freely express what they feel and think about products, services, and firms. Analyses of such large-scale textual data can uncover consumer motivations that have not been previously defined, especially in new economy settings such as the sharing economy. Collecting textual data is also relatively easy as consumers do not have to respond to long numeric scale items and can decide what and how much to write. Textual responses can also simultaneously capture multiple existing motivations in consumer minds, while manipulation and measurement often capture one motivation (or a few motivations at most).

To address the second challenge of understanding the long-term downstream consequences, firms can incorporate these extracted motivations into customer analytics. By combining the extracted motivation variables into their traditional dataset, firms can better identify the role and the impact of motivations that goes beyond the traditional predictive variables. This better helps them understand customers' transaction patterns, relationship and interaction with firms.

Using both the hosts' open-ended textual data as well as their transaction data from one of the leading sharing economy platforms, Airbnb, we demonstrate how (1) consumer motivations can be detected, and (2) how different motivations relate to various consumer engagement behaviors as well as retention propensity, and to pricing. In doing so, we extend our understanding of the long-term downstream consequences of consumer motivations in the context of sharing economy.

Motivation in the Context of the Sharing Economy

Consumers are no longer mere buyers of products from a firm. Consumers who are motivated to share their possessions with other consumers can now profitably do so by using platforms and marketplaces that facilitate sharing. This so-called sharing economy is expanding globally, with some estimating it at a value of 15 billion in 2013 to 335 billion dollars in 2025 (PWC 2015). While there is some variation in defining the sharing economy - such that some firms do not involve monetary transaction (e.g., Couchsurfing), and some do not have physical limits in sharing (e.g., knowledge in Wikipedia) - the context of sharing economy we focus here is where firms provide service platforms and consumers become micro-entrepreneurs to serve other consumers in return for a small fee.

A good example of such sharing economy platform is Airbnb, which is a home/room rental service that has more than 1.5 million rooms available in 190 countries (Airbnb 2017). The company far exceeds the number of rooms or suites offered by traditional hotel giants such as Hyatt. Airbnb's market value is $31 billion, while Hyatt is valued at $7 billion (Fortune 2016). Uber, a ride-sharing service, another sharing economy company, provides services in 57 countries, which has already reached a market valuation of $18.2 billion whereas a traditional car-rental service, Hertz, was valued at $12.5 billion (Huet 2014). Sharing economy companies are emerging across different industries such as hospitality and transportation industries (e.g., Spinlister, Parkatmyhouse, Relayrides). These businesses are all based on the same idea that you can become an individual micro-entrepreneur by renting out or sharing your property – such as houses, parking spaces, tools, bikes and even clothes.

The sharing economy, however, is not exempt from challenges. As the number of sharing economy platforms increases, a central question surrounding the sharing economy concerns how to motivate customers from both sides to participate in the sharing economy. Firms struggle to find ways to identify and motivate individual consumers to become micro-entrepreneurs, and to keep them engaged on the platform. Given the small service fee that firms receive from each transaction, scaling up operations is critical, and firms rely heavily on acquisition and retention of these micro-entrepreneurs. A critical question in this context therefore concerns how to best motivate customers to share their possessions, so as to maximize their likelihood of engaging with the sharing platform and staying on it in the long-term.

Consumers participate in the sharing economy as micro-entrepreneurs for multiple reasons – to seek extra income, to resist and reject conspicuous consumption, to meet others, and to foster a collaborative community (Ozanne and Ballantine 2010). Other motivations include the

better use of resource "slack" such as empty rooms, cars, parking spaces and to redistribute goods (Benkler, 2004; Lamberton, 2015). Individuals on other sharing economy platforms, such as an open-source project on the web, also enjoy feelings of competence and these feelings drive the development of collaborative knowledge output (Lakhani and Wolf 2003; Nov 2007). Some companies, such as BlaBla Car, emphasizes the opportunity to meet people when carpooling for a long trip from one city to another. This intrinsic drive of enjoyment is a key feature of the sharing economy and makes it distinct from the traditional economy that primarily operates based on financial benefit (van der Heijden 2004; Lamberton 2016). As the sharing economy continues to grow, new motivations may emerge (Zervas, Proserpio, and Byers 2015). In the context of Airbnb, some hosts may be attached to their homes and derive enjoyment from sharing beautiful aspects of their home with others (Hamari, Sjöklint, and Ukkonen 2015). Such hosts are likely to cherish and value their homes. Other hosts may enjoy meeting guests from different cultures and regions whereas some others may be simply motivated to make money.

In the next section, we describe the data that we used to explore motivations of Airbnb hosts and show how these motivations relate to their (long-term) behavior.

Data

Airbnb (www.airbnb.com) is an online sharing economy platform where consumers share their homes with other consumers. Consumers who are interested in sharing their homes can create their own webpages and advertise their apartments or houses using text descriptions and pictures. They can also specify the types of amenities (e.g., air conditioner, kitchen), the size of the properties (e.g., the entire home, private room), the amount they charge per night and any additional surcharges (e.g., cleaning fee). Hosts can also set their personal calendar to receive

bookings for certain nights while blocking other nights (e.g., only receive bookings in the summer). Guests pay the host through the Airbnb platform and have the option to leave reviews and ratings on the website after their stay.

Table 1

Descriptive Statistics

Region	Proportion
North America	58.58%
Latin America	3.24%
Europe	24.93%
Australia	9.04%
Asia	2.84%
Africa and Middle East	1.21%
-others-	0.15%

Room Type	Proportion
Entire home/apt	60.36%
Private room	38.42%
Shared room	1.21%
Others	0.08%

	Mean	SD	Median	Min	Max
Number of words used to describe a property	362.88	278.75	303	0	9,652
Guest review rating	4.71	0.34	4.8	1	5
Number of amenities at a property	11.59	4.01	11	1	30
Number of nights open for booking per year	177.44	118.41	176.57	0	364
Number of reservations	33.57	48.95	16	0	1,215
Number of reviews received	21.34	31.77	9	0	657

We use two primary datasets in this paper. The first dataset compiles textual responses of 43,343 hosts who responded to an open-ended question ("Why did you start hosting?") posted on Airbnb from March 2013 to October 2014. The question was built into the site and popped up on the page when hosts logged into the site. The survey completion rate was 30%[2]. Of the total 43,343 host responses, our analysis focused on 25,290 lay hosts who have only one property listed on Airbnb. This is to avoid the remaining professional hosts, such as property managers, whose motivations and behaviors are different from that of lay individual hosts (Li, Moreno, and Zhang 2016).

The second dataset includes 593,503 reservation transactions data (January 2011 to October 2015) of these 25,290 lay hosts (See Table 1). The dataset includes details of each completed reservation: (1) information about each reservation (e.g., the reservation date, price, the number of nights a guest wants to stay, the total number of guests), (2) guests' reviews (e.g., ratings on features such as host's communications, property's cleanliness), and (3) rich details of the host and property, such as location[3] (e.g., state, country), the property type (entire home/private room), and amenities (e.g., air conditioner, doorman).

The transaction dataset provides details for the "successfully booked" nights. This, however, does not inform us about whether the remaining un-booked nights are due to a host's failure to receive booking, or the host's decision to block these nights from potential booking. Because of this ambiguity, we requested the company to share the daily-level property

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[2] One may question whether our dataset is subject to self-selection bias due to the fact that survey is likely to be answered by active hosts who login to the Airbnb website. A comparison of the current dataset with a control dataset with hosts that have not completed the survey, however, revealed no systematic differences between respondents and non-respondents (see Appendix 8).

[3] Analysis covered all hosts from regions that speak English as a native language and regions that do not speak English as a native language. Further analysis on demographics and reservation details for both the English-speaking and non-English speaking countries did not reveal any systematic differences.

availability information, and the company provided the daily-level information from January 2013 to May 2015, such that the dataset informs us whether each host opened or blocked each day. Because blocking a night is indicative of a host's disenchantment from the business, we later use this information to estimate host retention on the platform.

The next section describes how we use the first dataset - hosts' open-ended textual responses - to extract host motivations. Then the following section uses the second dataset to explore how these motivations are associated with their engagement behavior. The flow of the analysis in this paper is summarized in Figure 6.

Figure 6. The Order and the Type of the Methodological Tools

Employed in the Analyses
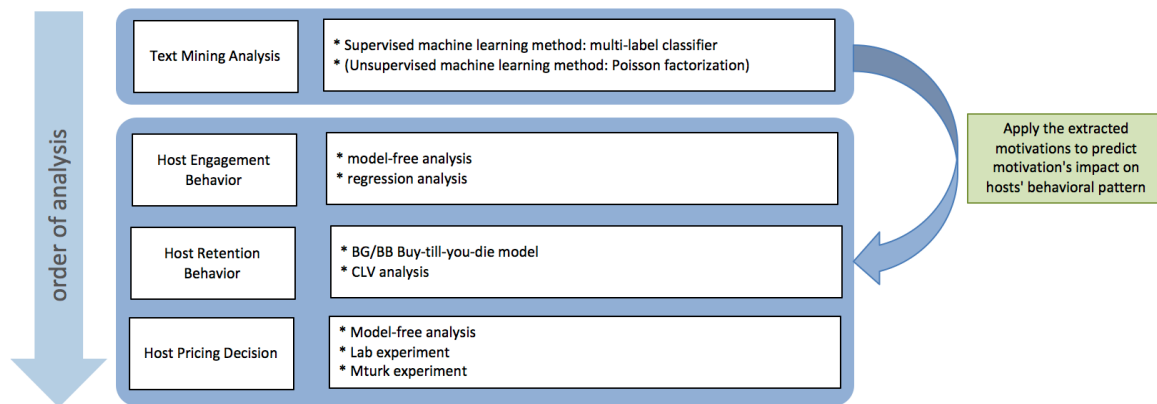
4.2. Extracting Motivations from Textual Responses

Two Approaches to Extract "Motivations" from Text

Firms can extract (latent) motivations from textual data using different machine learning tools. The choice of tools depends on whether a firm has a general insight on the content of the textual data, and whether the firm is willing to incorporate this prior knowledge to guide the machine learning process. For example, a firm may have partial insights on the content of the textual dataset - either through prior internal analysis, interviews, or focus groups. In such cases, the firm can use this prior knowledge to train supervised learning models. However, this approach is not feasible if the firm does not have prior knowledge or wishes not to incorporate prior insights, and prefers to automatically explore the latent topics. In this latter case, unsupervised learning methods, such as topic modeling, is more appropriate.

In our case, the company provided their insight on what they believe is the possible motivations of Airbnb hosts (Dataset 1: the textual responses to "Why did you start hosting?"). We therefore used their insight and ran the supervised machine learning method - the multi-label classification. We then additionally employed an unsupervised machine learning method, Poisson Factorization, to show the convergent validity of our findings across the two methods. Prior to running the two machine learning models, we pre-processed the textual responses following the standard steps in natural language processing. The details of the text pre-processing are described in Appendix 10.

Supervised Machine Learning: Multi-label Classification

Airbnb provided some knowledge on the potential set of motivations (see Table 2), identified by their consumer insights team. Leveraging these possible motivations, we applied a supervised multi-label classification model to identify existing motivations at an individual level, and found that 3 primary motivations – the motivation to earn money, to meet people and to

share beauty – robustly exist. Since a host can have more than one motivation (for example, a host can be motivated to both earn money and to meet others), this analysis employed a multi-label classifier (as opposed to binary classifier) because it simultaneously captures all possible motivations that can be held by a host. Details for the steps are described below.

Table 2

Definitions of Different Motivations

Motivations	Definition
Motivations	People host to aid their financial needs.
Earn Cash	People enjoy meeting guests from all over the world and from different cultures. They like to make friends.
Meet People	Sharing the beauty of a nicely maintained home, beautiful city and surroundings give happiness. People derive pleasure from giving recommendations and serving the needs of their guests.
Share Beauty	People encounter life circumstances (ex: they travel a lot, have an empty room/space, a roommate moved out etc.), and use this as an opportunity to host.
Life Circumstances	People had a positive experience as guests in the past and they want to offer others the same positive experience.
Pay Forward	Friends, family and other people who have been hosting recommended them to join and serve as a host.
Other's Recommendation	Other reasons that are not identified above.

Method. We first need to label a subset of the dataset to train a classifier, which will later be used to code the entire dataset. To label a subset of the dataset, we recruited MTurk human coders to read and classify the text responses using the seven pre-defined motivations provided by the company (Table 2). Human coders are often used as the most reliable source to interpret the meaning of text (Liu et al. 2012; Shiyan Ou, Khoo, and Goh 2008). Specifically, one hundred seventy Mechanical Turk workers (MTurkers) were recruited and paid $0.7 to evaluate 20 host responses from a random sample of 1,000 hosts from the survey responses. Upon starting the

survey, MTurkers were provided with a short description of Airbnb as a website where people can list, find and rent lodging. Participants were then informed that Airbnb is interested in identifying reasons why hosts offer their properties on Airbnb, and that their task is to read Airbnb host's survey responses to help the firm categorize host responses into different motivations. The following page of the survey then displayed the list of seven motivations along with the definition (see Table 2). Participants were asked to read each of the 20 text responses and categorize whether any of the 7 motivations are mentioned in each text. Note that each text can be labeled with more than one motivation. For example, upon reading the text, "I want to earn cash and also meet people from around the world," a MTurker can indicate that "earn cash" and "meet people" motivations are mentioned in the text. We randomly assigned text responses to MTurkers such that each text response would have a minimum of three MTurkers. Each text response was coded as 1 (otherwise 0) if 50% or more of the MTurkers indicated that a specific motivation was mentioned in the text (inter-rater coder agreement: $\alpha = .79$). Because the 1,000 host responses in the calibration dataset included professional hosts with more than one property, we used the 512 (out of 1,000) responses from hosts who have only one property as our calibration dataset.

Next, we used this human-labeled dataset to train the multi-label classifier. We applied the Binary Relevance (BR) method (Tsoumakas and Katakis 2008), which decomposes a multi-label learning task into multiple independent binary classification tasks, fitting one binary classifier for each motivation against all the other motivations. Support Vector Machine (SVM) with linear kernel was used to train the multi-label classifier.[4] To avoid over-fitting and to

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[4] The classification task was conducted using the scikit-learn 0.18 package in Python (http://scikit-learn.org/)

compare with other classifiers, we ran a 5-fold cross-validation to calibrate the classifier. Here, the occurrence of a word was based on the Tf-Idf measure[5]. After the classifier was calibrated, we applied it to the entire set of 25,290 textual responses of lay hosts. This enables us to discover whether each host has any of the one or more of the seven motivations.

Table 3

The Performance of Multi-label Classification

Motivation	Human labeled	Multi-label classification			Hit-rate		Jaccard index	
	Percentage	Percentage	AUC	Correlation with human coding	In-sample	Out-sample	In-sample	Out-sample
Earn Cash	58%	51%	0.94	0.97	99%	87%	0.97	0.78
Meet People	37%	35%	0.92	0.97	99%	85%	0.98	0.66
Share Beauty	20%	22%	0.84	0.93	98%	83%	0.90	0.41
Life circumstance	42%	44%	0.81	0.92	96%	73%	0.91	0.52
Paying forward	16%	17%	0.81	0.92	98%	80%	0.92	0.30
Other's recommendations	7%	4.4%	0.78	0.99	99%	94%	0.99	0.13
Others	13%	10%	0.66	0.95	99%	83%	0.93	0.10

Note-. Area Under Curve (AUC) of Receiver Operating Characteristic (ROC) curve, a measure commonly used for prediction accuracy of binary outcomes was used for the held out predictions accuracy using (see Appendix 9 for additional details; Hanley and McNeil 1982). The Jaccard index is defined as the number of correctly predicted motivations divided by the sum of the number of motivations that were labeled by human coders but missed by the prediction from the classifier, motivations that were predicted by the classifier but were not labeled by human coders, and the correctly predicted motivations.

[5] Tf-Idf (term frequency-inverse document frequency, Salton and Buckley, 1998) is a commonly used measure in information extraction, which measures the weighted occurrence of a word in a response given the frequency of the word appearing in responses of all respondents and the length of the textual response.

Results and discussion. Table 3 summarizes the performance of the supervised multi-label classification analysis. The second column shows the proportion of each motivation based on human-labeled dataset, which is indicative of the "true" proportion of each motivation. Note that the proportions do not add up to 100% because each host can have more than one motivation (see Appendix 11 for the combination of motivations).

A number of measures in Table 3 reveal high performance of multi-label classifier. The three motivations, "Earn cash," "Meet people," and "Share beauty," have the highest levels of predictive accuracy with Area Under the ROC curve[6] (AUROC) above 0.84. The other motivations also have accuracy greater than 0.7, suggesting a statistically acceptable prediction accuracy. The in-sample and out-of-sample hit-rate, averaged across the 5-folds, also suggest high reliability of the classifier. Similarly, strong predictive accuracy is revealed using the Jaccard index (Netzer et al. 2012; Toubia and Netzer 2016), which measures the similarity between two binary vectors.

The next section describes another machine learning method, which is "unsupervised" in nature. This approach does not require prior knowledge (from the firm) to guide the learning process.

Unsupervised Machine Learning: Poisson Factorization

We adopted an unsupervised topic modeling approach, Poisson Factorization, which examines the combinations of words to infer latent topics. This is a useful tool when firms do not have pre-existing knowledge about the latent topics. Our choice of Poisson Factorization was

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[6] Receiver Operating Characteristic curve (i.e., ROC curve) is a graphical plot of binary classifier's true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. The Area Under the curve (i.e., AUC) is a commonly used classification prediction accuracy measure. To see the ROC graph, see Appendix 9.

primarily driven by its quantitative advantages - it outperforms alternative topic modeling

methods (such as LDA) on sparse and short textual responses (Canny, 2004; Gopalan, Hofman,

and Blei, 2013), and it identifies probabilities of all potential motivation dimensions without

assuming a tradeoff of probabilities between motivations (i.e., such that all probabilities need to

sum up to 1).

Methods. Poisson Factorization assumes that each text is constructed of a mixture of

multiple topics with a Gamma prior, and the occurrence of words in each text are

probabilistically related to each topic with a Poisson distribution (Blei, Ng, and Jordan 2003).

We used the variational inference algorithm to estimate the model (Gopalan, Hofman, and Blei,

2013; Blei et al. 2016), and set the shape and rate hyper-parameters for both the word-topic

distribution and the document-topic distribution as 0.3 (Blei and John Lafferty 2009; Wallach et

al. 2009).

One of the most important decisions in topic modeling is to select the number of topics

and evaluate the quality/interpretability of these topics. We select the number of topics using the

perplexity score of held-out sample (Blei et al., 2003). Specifically, we split the entire dataset

(25,290 texts) into the training (80%) and testing (20%) dataset, and set the number of topics

from 2 to 15. The optimal number of topics based on perplexity alone is 15 topics, however,

some of these topics represent very similar meanings, making it difficult to interpret what each

topic stands for. Hence, we incorporate human judgment to interpret all the models and choose 6

topics. The words associated with each topic are easily interpretable and reflective of each

motivation (for the 6 topics, see Table 4) and the perplexity of the 6 topics model is only 12.25%

worse than the perplexity of the 15 topics model. This method is based on recent research that

addresses the peril of solely relying on the semantical coherence of inferred topics, because held-out sample performance (e.g., perplexity) may not reflect the "true" number of topics (Chang et al. 2009); hence, human judgment is further incorporated to assist the procedure of selecting the "optimal" number of topics.

Table 4

Poisson Factorization: The Associated Words for Each Topic

Motivation (Topics)	Top 10 words
Earn cash	money extra make cash income people meet little earn room
Meet people	people new love like meet meeting world enjoy hosting way
Share beauty	home share others beautiful area live enjoy stay love offer
Better resource utilization	apartment time rent travel empty away house lot place use
Situational force	help pay income home rent vacation cover need costs house
Others' recommendation	guest great guests friend try decided hosting experience friends good

Results and discussion. Using Poisson Factorization, we identified six motivations: earn cash, meet people, share beauty, better resource utilization, situational force, and others' recommendation. Poisson Factorization generates a list of the words associated with each topic (see Table 4). We examined the occurrence of words in each text to assign the probability to which each motivation exists in each text. For example, upon reading "I want to earn money and make friends from around the world", the Poisson Factorization analysis would generate the probability of each motivation in the text (e.g., cash: 0.60, meeting people: 0.55, sharing beauty: 0.10, situational drives: 0.15, opportunistic trial: 0.05, others: 0.00).

Insights from both the Supervised- and Unsupervised Machine Learning Analyses

Together, the Multi-label Classification and Poisson Factorization analyses suggest that earn cash, share beauty and meet people are the 3 main motivations that robustly exist in hosts' minds. We excluded the other three motivations – life circumstances, paying forward, others'

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recommendations – initially suggested by the company as they have vague definition and/or they only compose a small proportion of motivation in the text. We also excluded the three motivations – better resource utilization, situational force, and others' recommendation – - uncovered by the Poisson Factorization as they fail to surface in the multi-label classification analysis. The convergent validity of the two analyses is reported in Appendix 15A.

From now on, we will focus on the 3 common motivations that arose from both machine-learning results. There are a few points to emphasize before proceeding to any further analyses.

First, we want to highlight that these 3 motivations are the "primary" motivations. While everyone gains financial benefit in return for their hosting service and therefore one may argue that every host is driven by monetary reason, we treat this as a baseline benefit that led them to register as Airbnb hosts. Importantly, we argue that 3 primary motivations that hosts explicitly expressed as reasons for hosting in the text survey are what drive their everyday hosting decision, such that some hosts are more driven by the desire to "earn cash" than the others, while some others are more driven by the desire to "meet people" and/or to "share beauty." Second, we want to emphasize that our analyses focus on the distinctive effects of the 3 primary motivations on hosting behavior, without considering the interaction of these motivations. This is because our specific interest in this paper is to identify unique effects of motivations on host behavior, rather than comparing the two-way or three-way interaction effects of these motivations. Third, we use the motivation coding generated from the supervised multi-label classifier to see the motivations' impact on host behavior. Then we examine if the same pattern of finding emerges when we use the motivation coding generated from the unsupervised Poisson Factorization. The results from the multi-label classifier is reported in the main body of the paper, while the results from the

Poisson factorization is reported in Appendix 15 due to space limit. Both methods yield similar results.

4.3. Downstream Consequences of Host Motivations

Host Engagement and Retention

We now explore how the 3 main motivations (earn cash, share beauty, meet people) are associated with hosts' distinct engagement behavior, as reflected in their reservation history, property advertisements and retention propensities. Specifically, we predict that hosts who derive pleasure from "sharing the beauty" and "meeting people" are more engaged than those who are motivated to achieve their financial goal by "earning cash." This prediction is based on self-determination theory (Deci 1972; Ryan and Deci 2000) that suggest that an activity based on personal enjoyment is an intrinsic motivation, and is volitional, self-determined and autonomous (Kehr 2004). Intrinsic motivation leads individuals to stay more engaged and perform better (Deci 1972; Ryan and Deci 2000). Building on self-determination theory, research on collaborative consumption also argues that the enjoyment of an activity is a key intrinsic motivation that drives the collaborative economy aside from the extrinsic motivation to earn cash. This argument has also been manifested in other collaborative consumption contexts, such as transferring goods (e.g., sharetribes.com), knowledge sharing, and open source software repositories (e.g., Github) (Hamari, Sjöklint, and Ukkonen 2015).

Based on this prior literature from both the self-determination theory (Deci 1972; Ryan and Deci 2000) and collaborative consumption research (Ozanne and Ballantine 2010; van der Heijden 2004), we predicted that the motivation to "share beauty" and to "meet people" are intrinsic motivations, while the motivation to "earn cash" is an extrinsic motivation. However,

one may argue that the motivations to "share beauty" and to "meet people" are also extrinsic, as people use the hosting experience to satisfy their own needs.

In the following analysis, we aim to empirically answer this question through the behavior outcomes of these motivations. Intuitively, if these two motivations (share beauty, meet people) are indeed extrinsic, then hosts with these motivations should behave similarly as hosts who are driven by monetary incentives. On the other hand, if these two motivations lead to greater host engagement, it is indicative that the two are more intrinsic motivations. Now, let's turn to the dataset and examine the impact of motivations on host engagement.

Host engagement. We first present some descriptive analyses of host engagement by the 3 motivations. Each of these 3 motivations was binary-coded based on the multi-label classifier[7], and this binary-coding reflects whether a host has (vs. does not have) each of the 3 motivations. To better contrast the impact of each motivation on host engagement, we first examined hosts with only one of the three motivations (see Table 5). Host engagement is measured using the number of words used in a property ad, the number of photos, and the number of nights opened per year for potential booking.

Table 5

Engagement of Hosts with Different Motivation Identified from Multi-label Classification

Motivations	Number of Words used to Describe a Property	Number of Photos	Nights Active per Year
Earn Cash	339.38	15.77	160.25
Meet People	379.33	16.55	193.60
Share Beauty	379.74	17.49	180.65

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[7] For brevity of the manuscript, we report the results based on motivations extracted from multi-label classification in the text. We replicate all downstream consequences analysis, including host engagement and retention, and host pricing strategies, with motivations extracted from Poisson Factorization, and find strikingly consistent results. For all results using Poisson Factorization, see Appendix 15B.

Table 5 results reveal that hosts who are motivated to share beauty and to meet people are more engaged than those who are motivated to earn cash. They used more words to describe their homes on Airbnb, posted more photos to advertise their home, and opened more number of nights to receive booking. For hosts with more than 1 motivation, see Appendix 12.

While our initial findings from the model-free analyses are intriguing, they are susceptible to an alternative explanation that different property traits elicit different motivations. For example, hosts in smaller homes may have more social interaction with guests, which can lead them to report that they are hosting to "meet others." In support of this explanation, the majority of hosts who indicated that they want to "meet others" were, in fact, renting out a private room (58.45%) as supposed to entire home (39.58%; see Appendix 12 for the relationship between property traits and motivation type). If this is the case, it is the property types that drive hosts' engagement pattern, rather than the motivations driving their engagement pattern. If this is the case, it is the property types that drive hosts' engagement pattern, rather than the motivations driving their engagement pattern.

We respond to this concern both empirically and theoretically. First, we empirically find a consistent pattern of results when controlling for an extensive list of property characteristics: including room types (i.e.., renting out the entire home/ private room/ shared room), the average number of guests per reservation, the average nights per reservation, the total number of amenities, amenity types (e.g., wireless internet, free parking, allows smoking, allows pets, cable, breakfast) and the average price of the same room type within the region (i.e., city) (For details, see Appendix 14A). Here we include hosts who have more than one motivation, and the binary coding of each motivations per each host helps us examine the distinctive effect of

motivation. Second, our findings are theoretically consistent with the well-established consumer behavior theory on self-determination theory (Deci 1972; Ryan and Deci 2000). This theory suggests that extrinsically motivated individuals are less engaged than intrinsically motivated individuals, which is consistent with what we find between cash-motivated individuals versus meeting-people and sharing-beauty motivated individuals. While the goal here is not to parcel apart whether property traits or the motivations come first, we reveal that the identified motivations serve as a reliable proxy to predict host engagement pattern.

Now, let's extend our model-free findings on hosts' engagement to retention behavior. Model-free evidence: retention behavior. Here we show whether motivations predict hosts' long term retention likelihood. First, our model-free analysis focused on hosts that have only one of the three motivations to show the distinct effects of motivations on retention. The dependent variable is whether these hosts continue to open their calendar at least once a month with a progress of time. Not surprisingly, Figure 7 reveals that there is a general declining trend across all 3 motivation groups. More interestingly, hosts who were motivated to earn cash showed a steeper decline in their tendency to open the calendar compared to hosts who are motivated to share beauty or to meet people. This again reflects the same pattern of findings in the engagement section

However, this analysis is subject to the criticism that it is only examining hosts with 1 motivation, which leaves out the possibility that hosts with multiple motivations behave differently. Second and more importantly, a host's decision to close the calendar is "latent" such that the closed calendar may either reflect his/her decision to intermittently rent out (e.g., rent out only in the summer), or to fully quit hosting. These two decisions are hard to disentangle because hosts usually do not send explicit "exit" signals by removing property profiles or cancelling their

host account; they simply become dormant. To address these concerns, the next analysis applies

a buy-till-you-die model. This retention model uses the 3 motivation variables as predictors, and

takes account the "latent" nature of the rent decision. Hosts with not only one, but multiple

motivations are all included in this analysis.

Figure 7

The Proportion of Hosts who Posted at Least Once within a Month
(i.e., a host is active)
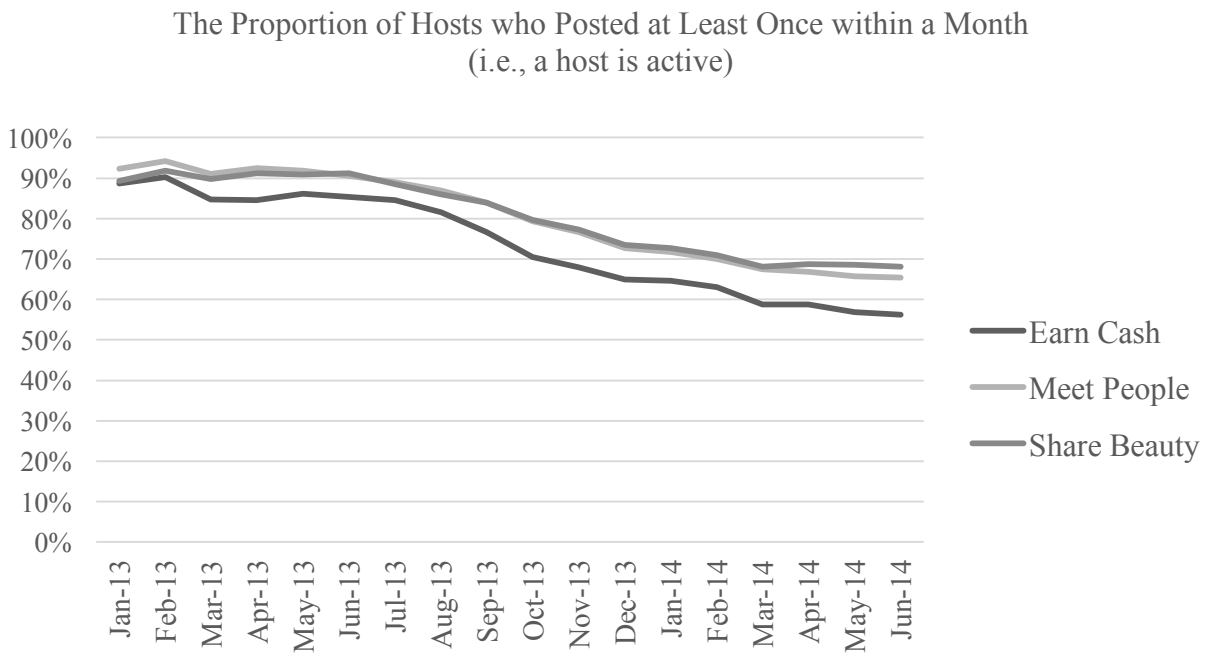
Note -. This dataset is based on the subset of the daily-level transaction data from January 2013
to June 2015 (see data description section in the introduction). The graph reflects the proportion
of hosts who joined the Airbnb platform sometime between Month 1 to Month 6 (January 5th,
2013 to May 31st, 2013). The declining graph after the June 2013 suggests hosts' general
declining activity level; hosts who were motivated to earn cash showed the greatest likelihood to
churn. Hosts who are motivated to share beauty and to meet people, on the other hand, were less
likely to post.

Buy-till-you-die model. As described in the data section, we use the daily property

availability information of 5,485 hosts (from Jan, 1 2013 to May, 31 2015) to see if hosts opened

or closed each calendar date. To model host retention, we adopt a buy-till-you-die approach

(Schmittlein, Morrison, and Colombo 1987) using the Beta-Geometric/Beta-Binomial (BG/BB) framework at discrete time in a non-contractual setting (Fader, Hardie, and Shang, 2010). This model simultaneously predicts a host's propensity to churn and the probability to open at least one night in a month.

Model specification. We assume that in each period t (i.e., month), host i has a latent state of attrition z_{it}, where $z_{it} = 0$ if the host is "alive", and $z_{it} = 1$ if the host has "churned." A host is always alive when s/he first activates an Airbnb account to make the property available, thus $z_{i0} = 0$ for all hosts. For each of the upcoming months t, host i makes two simultaneous decisions: the decision to stay "alive" (vs. churn); and the decision to open (vs. not open) any calendar nights while "alive." We define host i's probability of churning in period t as θ_{it}:

$$P(z_{it} = 1|z_{it-1}) = \begin{cases} \theta_{it} & \text{if } z_{it-1} = 0 \\ 1 & \text{if } z_{it-1} = 1 \end{cases} \qquad i \in \{1, \dots, I\}, t \in \{1, \dots, T_i\} \qquad (1)$$

We denote y_{it} as an indicator of availability of host i, such that $y_{it} = 1$ if the host opens a property at least one calendar night in month t, and $y_{it} = 0$ otherwise. While alive, host i makes the property available for booking on month t with probability pit. T_i is the number of months that host i is observed in the data. y_{it}More formally:

$$P(y_{it} = 1|z_{it}) = \begin{cases} p_{it} & \text{if } z_{it} = 0 \\ 0 & \text{if } z_{it} = 1 \end{cases} \qquad i \in \{1, \dots, I\}, t \in \{1, \dots, T_i\} \qquad (2)$$

Further, the latent churning probability θ_{it} and the availability probability p_{it} are modeled as:

$$\theta_{it} = \text{logit}^{-1}[\alpha_i^\theta + \alpha(cash_i, \ sharing_i, meeting_i)],$$

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and
$$p_{it} = \text{logit}^{-1}[\alpha_i^p + \alpha(cash_i,\ sharing_i, meeting_i)]. \tag{3}$$

where,
$$\text{logit}^{-1}(\text{x}) = \frac{1}{1+\exp(-x)}. \tag{4}$$

Hosts' churning and availability probabilities are determined by the observed heterogeneity from motivations that is captured by function $\alpha(\cdot)$, as well as unobserved heterogeneity (α_i^θ and α_i^p). Separating the observed from the unobserved heterogeneity helps us infer the effects of the 3 motivations on hosts' churning decision, and rule out other potential explanations driven by individual differences such as gender, property size or location.[8] The individual likelihood function of observing as sequence of month-availability of host i is further defined as:

$$P(y_{i1}, y_{i2}, \dots, y_{iT}) = (\prod_{\tau=1}^{tx_i} p_{i\tau}^{y_{i\tau}}(1-p_{i\tau})^{1-y_{i\tau}}(1-\theta_{i\tau})) \times \sum_{t=tx_i+1}^{T_i+1} (\theta_{it}^{I\{t \le T_i\}} \prod_{\tau=tx_i+1}^{t-1}(1-$$

$$\theta_{i\tau})(1-p_{i\tau})) \tag{5}$$

Note that tx_i is the period of the last observed available month of host i. The churn rate (θit) and the open rate (pit) are calculated based on equation (3) and (4).

Table 6

Coefficients from the Retention Model

Motivations	Intercept (unobserved heterogeneity)	Earn Cash	Meet People	Share Beauty
P(churn)	-3.827*	.259*	-.142*	-.163*
P(active)	1.600	.117*	-.100	-.054

[8] Similar to the controlled variables in the host engagement section, we control for this using individual-difference intercept to capture the "true" effect of motivation.

Results and discussion. Results are consistent with the findings on engagement (Table 6). Having the motivation to meet others and to share beauty led to significantly lower tendency to churn from the platform (i.e., coefficients: -.142, -.163 respectively). On the other hand, having the motivation to earn cash led to a greater tendency to churn (i.e., coefficient: .259). Interestingly, the motivation to earn cash led hosts to actively open their calendar "while" they are still active on the platform (i.e., coefficient: .117). This together suggests that the desire for cash motivates hosts to actively open up their homes, but also make them decisive to churn[9]. Similar results arise when using motivation coding from the Poisson Factorization (Appendix 15C).

One concern of the inferences in the buy-till-you-die model is that host motivations are inevitably confounded with their property traits. We admit that host motivations cannot be fully isolated from property traits; in fact, certain motivations, such that sharing beauty naturally rely on the high-quality property traits. To address this concern, we used motivations as dependent variable and used all available property characteristics in our data as predictor in a regression analysis (For details, see Appendix 14B), and found that variables such as the number of listing description words, host profile photos, free-parking and breakfast, are significantly different between the three motivations. However, we did not find systematic differences of motivations in property characteristics, such as the availability of gym, Jacuzzi, dryer, and pool. In this sense,

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[9] We compared the current model with a baseline model without motivation variables. In the baseline model, host heterogeneity comes only from unobserved idiosyncratic factors (α_i^θ and α_i^p). Watanabe-Akaike Information Criterion (WAIC; Watanabe 2010) - a measure of model fit - for the baseline model is 77525.94, and the model with the motivation variables is 77478.29, reflecting a better model predictability in explaining hosts' churning and engagement behavior.

we argue that the effects of motivations on host retention are not driven by particular property traits in a systematic way.

These findings reveal unique effects of motivation on retention. To understand the importance of discovering host motivations from the firm's perspective, we now examine the financial value that Airbnb could capture, when the company has (vs. does not have) the information on motivation. Accordingly, we used the coefficients of each motivation in Table 6 to compute hosts' expected customer-lifetime-value (CLV; Table 7) for each motivation group over a 36-month period. We first explored the extent to which each motivation leads to greater likelihood to be alive on the platform. As expected, while hosts that have none of the three main motivations stay alive for 24.80 months in the 36-months simulation period, having the motivation to share beauty and to meeting people respectively led to 1.25 and 0.72 longer months of stay. Having the motivation to earn cash led to for 1.76 shorter months of stay. Also, the motivation to share beauty and to meet people led to greater number of opened calendar months.

Table 7

Host CLV per Motivation using Multi-label Classification

	Intercept	Earn Cash	Sharing beauty	Meeting people
# of Months Active	24.80	23.04	26.05	25.52
# of Months Open	15.41	14.49	15.78	15.47
Expected CLV with Motivation ($)	15,230	13,770	14,750	12,880
Expected CLV without Motivation ($)		14,150		

Note – Baseline is the group of hosts with none of the three main motivations. For details of the expected CLV simulation process, see Appendix 15D. The company receives around 3-4% of the amount indicated above.

One may base on this finding to predict that the motivation to share beauty and to meet people lead to higher CLV than the motivation to earn cash. Counter to this prediction, however,

we found that only the motivation to share beauty that leads to higher CLV, while having the motivation to meet-people leads to lower CLV (see Table 7). This finding seems at odds with our previous results that both motivations (share-beauty and meeting-people) increase host engagement.

To understand this puzzling result, we need to consider the fact that CLV is not only driven by the number of opened nights (which is the estimates of buy-till-you-die model), but also the successfully booked nights and the price charged by each host. Here, we find that hosts driven by these two motivations (sharing-beauty, meet-people) had equally successful booked nights, however, hosts motivated to meet people charged much lower prices.

We also want to highlight the benefit of incorporating motivations in the CLV calculation. Using the estimates of the baseline buy-till-you-die model (refer back to footnote 8), we followed the same simulation steps and calculated the expected CLV without incorporating the 3 motivations. In such case, each newly acquired hosts would generate an average of 14,150 dollars in a 36-months period (see last row in Table 7). However, this dollar amount is less accurate because the number can be an overestimate or an underestimate, depending on the latent motivations of a host. At a firm level, the company can project a more accurate CLV only if they what proportion of hosts have each of these motivations.

4.4. The Pricing Decision by Motivations

In the previous section, we revealed that CLV is uniquely driven by the price charged by each motivation group. In this section, we further explore this idea and show that hosts who are motivated to share beauty charge more than the other hosts. We also show that those who are motivated to meet people charge less than the other hosts.

This prediction is based on the prior literature that home owners who put subjective and emotional valuation on top of the objective valuation inflate the price (Genesove and Mayer 2001). On the other hand, hosts who are motivated to meet others are likely to price lower, as lower price increases demand (Gale 1955). While we predict the two opposing pricing decisions among those sharing-beauty and meeting-people motivated hosts, the cash-motivated hosts would price their home somewhere in between these two groups.

Model-free Evidence on Pricing Decision

We first examined the transaction dataset to explore how hosts with different motivations adopt different pricing decisions. The price per night was calculated by adding the property price including the base price (i.e., for the total duration of the stay), extra price (i.e., cleaning fee) and guests' service fee paid to Airbnb.

Using the motivations extracted by the multi-label classification, we examined hosts that hold one of the three motivations. Analysis revealed that the average price is the highest among hosts motivated to share beauty ($M_{sharing\ beauty}$ = \$198.39) and the lowest among those motivated to meet people ($M_{meet\ people}$ = \$128.34). The price of those who were motivated to earn cash lay in the middle (M_{cash} = \$183.78). The average prices across the three groups are significantly different from one another (cash vs. sharing beauty: p <.01, cash vs. meeting people: p < .001, sharing beauty vs. meeting people: p < .001).[10]

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[10] This analysis is based on the motivation classification based on the multi-label classifier. Similar results were obtained when comparing prices for hosts with motivations based on the Poisson Factorization or the sample of human coded hosts (Appendix 15F).

While these findings are intriguing, the observed pattern may also be explained by other factors such as accommodation size, amenities, and location (e.g., New York City is higher priced vs. Iowa City). For instance, hosts who live in luxurious properties are likely to not only report that they want to share the beauty of their homes, but also charge higher price because of their "objectively" superior property. On the other hand, hosts who can only rent a room in their apartments are more destined to interact with their guests, and thus report that they want to meet others but also charge lower price per night. That is, the qualitative property differences, as opposed to motivational factors, may drive the different pricing decisions. To address this concern, a number of property traits, such as advertisement types (e.g., number of words used to advertise a property, whether host has a profile photo), amenities (e.g., kitchen, doorman, gym) and guests' star ratings (e.g., cleanness, location, star ratings) were used as control variables, and the three dummy-coded motivation variables were included in a regression analyses. The pricing results remained consistent even after controlling for these variables (See Appendix 16). Despite the regression analyses showing the effect of motivations on pricing, the analyses are still vulnerable to alternative explanations such as the endogeneity between price and demand, and unobserved property traits. For example, even when both sharing-beauty and meeting-people groups indicate that they have a queen size bed, one might have an expensive Tempurpedic mattress while the other has a Walmart mattress. To fully control for these confounding variables and to see the impact of the 3 motivations on pricing, two follow-up controlled experiments were conducted. Here, we set property traits constant, and only manipulate (Experiment 1) or measure (Experiment 2) host motivations.

Experiment 1: Manipulating Motivations While Holding the Property Constant

Methods. The goal of Experiment 1 is to manipulate motivations while controlling for home amenities, and replicate the findings on host motivations and property pricing. We hold the property constant, thereby ruling out the alternative explanation that hosts motivated by sharing beauty charge more because they have better amenities. MTurk participants (N = 120) were randomly assigned to one of three conditions ("sharing beauty", "meeting people" and "cash"). Upon starting the experiment, all participants saw pictures of an apartment in Florida (see Appendix 17). Participants were then asked to imagine owning the apartment, and were asked to consider renting out a room in the apartment on the Airbnb website. To manipulate motivations, we asked participants to either describe how the Airbnb posting could help them share beautiful aspects of their home ("sharing beauty"), help them meet people from around the world ("meeting people"), or how it could help them financially ("earn cash"). All participants spent a minimum of 3 minutes on the description task. For the details on the manipulation instruction and the pretest results along with confound check measures, see Appendix 18. These details are omitted here due to space limit.

Next, all participants responded to two questions (α = .78): (1) "How much would you charge for this private room compared to other similar-quality rooms in the same region?" (7 point Likert scale:1= significantly lower, 4 = about the average price, and 7 = significantly higher), and (2) "What would be the appropriate pricing of your home, given that you have taken the market price into your consideration?" (7 point Likert scale: 1 = significantly lower, 4 = about the market price, 7 = significantly higher).

Results and discussion. The one-way Anova result shows a significant difference between the 3 motivations ($F(2, 117) = 8.30$, $p < .001$). Similar to the model-free pricing analysis from

the Airbnb dataset, this experiment revealed that hosts who are motivated to share beauty priced their home higher than those who are motivated by cash ($M_{sharing\ beauty}$ = 4.78, SD = .91 vs. Mearn cash = 4.40, SD = .71; $F(1, 117) = 6.34$, p = .025) and those who are motivated to meet people ($M_{meet\ people}$ = 4.06, SD = .66; $F(1, 116) = 16.59$, p < .001). Hosts who are motivated to meet people charged lower than those who are motivated by cash ($F(1, 116) = 3.95$, p = .049). This finding suggest that even when home property is the same across all participants, the differing motivations leads to different home price decision.

Experiment 2: Measuring Motivation While Controlling for the Property Type

Experiment 2 measures (rather than manipulates) individual differences in motivation, and employs a dollar-unit dependent variable. We intend to show that having the motivation to share beauty increases the price, while having the motivation to meet people motivation lowers the price.

Methods. Behavioral lab participants (N = 113) at a private East Coast university participated in this experiment. The cover story asked participants to imagine living in Chicago after graduation and renting out a room of their home on the Airbnb website. The set of property images in Chicago was shown to all participants (see Appendix 19). Participants were then informed that people differ in their reasons for hosting on the Airbnb website and were given the 3 motivations ("to share beauty", "to meet people", "to earn cash") along with the definitions of each motivation (See Appendix 20 for the description). Subsequently, all participants were asked to allocate 100 points across the 3 target motivations ("sharing beauty", "cash", "meeting people") to reflect how much weight they would put on each of the motivations when hosting on

Airbnb. The following page of the survey then asked them to set the price for the private room of their home shown in the picture. The price was constrained to reduce outlier such that the minimum price a participant could set was $20 and the maximum price was $250. On average, participants set $112.61 (SD = 47.01; min: $33, max: $250).

Table 8

Experiment 2. Regression Output

	B	error	Beta	t	Sig.
(constant)	111.89	7.51		14.90	.000
Meet People	-.53	.24	-.21	-2.19	.031
Share Beauty	1.22	.44	.26	2.77	.007

Note -. Dependent variable: price per night ($)

Results and discussion. The allocated points in each of the three motivations were used as predictors in a linear regression. The "cash" variable served as a baseline, and thus was excluded from the regression (see Table 8). The dependent variable was the price per night ($). Results again reveal similar patterns: each point increase in the "sharing beauty" motivation leads to $1.22 additional charge per night. In contrast, each point increase in the "meeting people" motivation leads to $0.53 lower charge per night.

Together, the regression analysis suggests that hosts who are motivated to share the beauty of their property set a higher price, while those who are motivated to meet people set a lower price, compared to those who are motivated to earn cash. This finding in the lab experiments confirms our pricing findings from the Airbnb transaction dataset. These pricing decisions may be driven by sharing-beauty-motivated hosts' desire to maintain the high quality

of their homes or a strong sense of endowment. The meeting-people motivated hosts may be willing to charge a low price to attract many guests.

4.5. Essay 2 General Discussion

This paper contributes to a small but growing body of research that bridges the consumer behavior and marketing science disciplines (Bell and Lattin 2000; Kivetz, Netzer, and Srinivasan 2004). Multiple methodological tools from both disciplines have been utilized, such as machine learning (multi-label classification and Poisson Factorization), latent attrition models, and controlled experiments. All of which come together to analyze consumer motivations on one of the leading sharing economy firms, Airbnb.

Findings suggest that Airbnb hosts who are motivated by sharing beauty and meeting others put more effort into describing their homes using more words and pictures, and opened more nights compared to hosts who are motivated to earn cash. Further analyses on host retention confirmed that these hosts (who are motivated to share beauty and to meet others) are also less likely to churn. Together, these two motivational drivers resulted in similar host engagement and retention patterns. However, the financial outcomes on the firm notably differed such that the motivation to meet people led to the lowest expected CLV, while the motivation to share beauty led to the highest expected CLV. This is because of the differences in motivational impact on hosts' pricing decisions. Two follow-up experiments confirmed that the pricing patterns still hold even when property types and amenities are controlled.

While these finding are intriguing, one may raise the concern that all hosts' true desire is solely to earn cash, and that some hosts are tactfully disguising this true motivation by expressing that their desire is to socialize or to be altruistic to others. This speculation seems plausible given that all hosts earn cash for their service on Airbnb. We address this concern in

several ways: first, if the only motivation is to earn cash, then each of the 3 motivations should lead to the same engagement, retention and pricing behavior. We, however, find consistent differences between these motivations. Second, our findings align with the self-determination theory in motivation research (Richard et al. 1997; Urdan and Schoenfelder 2006; Vallerand 1997) thereby providing additional support for our argument. Third, using counterfactual thinking, we can ask ourselves if there are people who wish to share their homes even when they do not earn money. Existing sharing platforms such as Couchsurfing are good examples of such sharing, and the existence suggests that there is a big consumer sector who are willing to share their homes even without any financial benefit. For many individuals, monetary transactions on Airbnb can be viewed as offering an assurance structure that facilitates the social exchanges between hosts and guests (Lampinen and Cheshire 2016).

This financial benefit does not necessarily crowd out the joy of social benefit and can actually facilitate such social benefit (Lampinen and Cheshire 2016). To better understand how the two motivations can create synergy, consider an analogy of two full-time researchers at a university. While one researcher may be working only to earn money, another researcher may be working because s/he enjoys research and likes to contribute to the field. This second researcher (of which we hope we all are) uses monetary compensation as an assurance tool, but this is not a motivating factor while pursuing daily activities. A similar analogy can be made with Airbnb where monetary compensation is a base for the operation but not the sole driving force for a host's behavior.

Methodological Contributions

The current research contributes to the consumer behavior literature by providing practical tools that academics and managers can use to extract consumer motivations. First, we proposed two machine learning tools (multi-label classification and Poisson Factorization) to extract motivation from open-ended survey responses. We found high convergent validity between the two approaches in identifying common motivations. As discussed earlier in the introduction, the two approaches can be flexibly used depending on how much prior knowledge firms have. For example, multi-label classification is more suitable when firms have some prior knowledge on latent topics that can guide the learning process. On the other hand, Poisson Factorization is more suitable when firms do not have prior knowledge or when the large scale of latent dimensions make a human-coded labeled dataset infeasible. Each of these methods acts as a useful tool in new marketing domains such as the sharing economy studied here, where consumer motivations are critical to the business and yet may be less clear. By proposing these two methods, we introduce practical tools to firms and encourage researchers to explore consumers' latent psychological traits and states (Matz and Netzer 2017).

Learning consumer motivations from textual data is also advantageous and can supplement numeric surveys or controlled lab experiments in traditional consumer behavior research. While traditional research is useful in proving theories and unveiling evidence of consumer psychology, it has limited applicability in the real world. The difficulty of using Likert scale survey questions for a large population, and the difficulty of manipulating motivations and their short-lived effects have limited the implementation. In addition, these traditional approaches accommodate only a single effect of motivation, making it difficult to accommodate a mix of several motivations that may collectively drive consumer behavior. The traditional

approaches also have prevented the extraction of latent motivations unbeknown to researchers, leading to only a partial insight for firms.

Subsidizing these traditional methods, machine learning approaches serve as data-archaeological tools to extract latent motivations using a bottom-up approach, and allow for the flexibility of identifying multiple motivations simultaneously. Practically, these methods also help firms save time and financial costs by reducing the burden of conducting long numeric surveys to a large set of customers. By running open-ended surveys, firms also give consumers freedom on what and how much to write. If firms decide not to run independent surveys, they can also easily utilize existing textual data, such as customer reviews on firm's webpage, commercial websites (e.g., Amazon, Yelp, BestBuy), and/or consumer blogs.

Using machine learning tools to understand customers' latent psychological traits opens new doors for multiple industries. For example, using simple open-ended surveys, real estate sectors (e.g., Zillow) can identify reasons for the influx/exit of home-buyers in a neighborhood (e.g., good school district, nature, privacy, noise level). Headhunting agencies can identify individuals' motivation behind their search and relate their motivation(s) to the length of their stay on a new job, the amount of income, and their long-term career success. Our insights also apply to sectors in public policy. Educators in K-12 can use students' verbal responses in the form of a short essay or interview, which would be especially useful given that young students have difficulty comprehending long Likert-scale numeric survey questions. Future research can also explore additional sources of information besides textual data, such as Facebook pages (Schwartz et al. 2013). Extracting motivations from textual responses also allows researchers to study multiple motivations of the same customer. We believe that such approaches open the opportunity to study the interaction of an array of motivations in other settings.

Our research also contributes to the consumer behavior literature by employing a diverse set of methodologies beyond machine learning tools. These methodologies include probabilistic latent attrition model and controlled lab experiments. Having the flexibility to adopt different tools extends the conventional research paradigm that heavily relies on lab experiments. We also address the limitation of typical econometric models using transactional data, which often ignores "soft" aspects such as motivation in consumer psychology. The utilization of these methods, therefore, provides a good example of how to bridge quantitative analysis and consumer behavior research in the field of marketing.

Contributions in the Context of Sharing Economy

Our research also contributes to the growing literature on sharing economy. While the concept of traditional economic transactions between company and customer has been prevalent within market structure, the idea that the company serves as a platform and customers interact with each other to generate revenue is an emerging market phenomenon (Botsman and Rogers 2010; Hamari, Sjöklint, and Ukkonen 2015; Heinrichs 2013; Lamberton 2016, 2015).

Most sharing economy research up to now has been limited to the conceptualization of the sharing economy, running analyses on small samples of survey responses and in-depth interviews, relying on independent data collection either by recruiting a sample of hosts, utilizing government data (Zervas, Proserpio, and Byers 2015), scraping data (Ert, Fleischer, and Magen 2016; Li, Moreno, and Zhang 2016) or by conducting case studies from user forums (Rosenblat and Stark 2016). Building on this growing literature, this paper is one of the first papers to use big data in the context of the sharing economy (for exceptions see two unpublished manuscripts: Fradkin 2017; Fraiberger and Sundararajan 2015). Not only do we conceptually emphasize

customers' new role as hosts who generate profit for the firm, but also we use empirical findings to provide managerial insights on host engagement, retention probability, the long-term CLV and pricing decision. Importantly, we not only utilize transaction datasets but also extract psychological traits (i.e., motivations) from textual data, thereby revealing the importance of understanding psychological traits. No research so far has empirically extracted the motivations and showed the prevalence and robustness of identified motivations in relation to consumer engagement in the context of the sharing economy.

The identification of the 3 motivations also benefit from the conceptual distinction of intrinsic versus extrinsic motivation in self-determination research (Deci and Ryan 1985). The definition of intrinsic versus extrinsic motivation (Richard et al. 1997; Urdan and Schoenfelder 2006; Vallerand 1997) has been applied to understand consumer motivations in the recent sharing economy literature (Bock, Kim, and Lee 2005; Hamari, Sjöklint, and Ukkonen 2015; Nov, Arazy, and Anderson 2011). For example, Hamari et al. (Hamari, Sjöklint, and Ukkonen 2015) view the enjoyment of sharing as intrinsic, and the economic benefit in sharing economy as extrinsic. Similarly, collaborative knowledge sharing platforms are operated by those who derive enjoyment from the reciprocal relationship and affirmation of self-worth both of which are intrinsic, while receiving external reward(s) from the collaboration is extrinsic (Bock, Kim, and Lee 2005). Building on this classification, we empirically demonstrate that sharing beauty and meeting people are likely intrinsic motivations, whereas earning cash is an extrinsic motivation. We also show both the short and the long term behavioral consequences of these motivation categories in the Airbnb setting.

One may question why the monetary incentive (extrinsic) does not crowd out the social motives (intrinsic), which seems to contradict some of the prior scholarly findings (Deci,

Koestner, and Ryan 2001; Heyman and Ariely 2004). What differentiates our context is that prior research examined contexts in which researchers provide a "fixed amount" of reward and see how it affects people's engagement. By contrast, we treat both the amount of the reward ($) and host engagement as outcomes. That is, the amount of reward is not predetermined by a researcher, but is a host-determined.

Our findings also provide practical implications for the firm, Airbnb. Acquiring and retaining hosts is of major importance to the platform for their survival. Given the heterogeneity in motivations, the company should diversify their approach to acquire potential customers. Only emphasizing the financial benefit may not attract those whose primary motivation is to meet others or to share the beauty of their homes. Addressing these opportunities would be more appealing to heterogeneous consumer groups. The company can also have a better understanding of host retention propensities, leading to a more accurate evaluation of CLV by motivation groups.

Future Direction

As with any research there are several limitations to our data and analysis that can be explored in future research. First, given that we only collect survey responses once to capture hosts motivations, our assumption of the motivation in this research is rather static. However, it is possible that consumer motivation is dynamic in terms of both the strengths and/or the types of motivation. To partly address this question, we examined text from hosts who have just joined (less than 1 year) and filled in the text survey, and compared their motivations with those who have already hosted for 1-2 years, and for 2-3 years prior to completing the survey. Results suggest that the length of hosting experience did not affect the general proportion to which each

motivation was mentioned in the text, suggesting that motivations appear at the same ratio across time spans. Nonetheless, this analysis only provides crude proxy for motivational dynamics. We encourage future research to explore such dynamics with multiple measures of motivation over time.

Second, one may be curious to find out the generalizability of our motivation findings in other types of customer-firm relationship. We believe that the 3 main motivations in our dataset are unique to Airbnb, and that different sets of motivations are likely to arise for different companies and industries. For example, Uber drivers likely have the motivation to earn cash where they pick up riders at lower rates than those in the traditional economy (e.g., vs. high price of Yellow Cabs in NYC) (Wallsten 2015), but it is less likely that an Uber driver would be motivated by sharing the beautiful interior of their cars. Likewise, different firms are likely to have a unique set of consumer motivations. For these reasons, we encourage more sharing economy platforms and firms to adopt our tools to identify their own set of consumer motivations.

Third, the 3 major motivations from the textual survey responses may not fully represent truthful responses. Further, the survey responses do not capture the weight of each motivation, such that there is no clear distinction between a host who is 80% driven by cash and 20% driven by the motivation to meet people, and a host who is driven 20% by cash and 80% to meet people. The only proxy we can use is the frequency with which each word appears in a text. However, because our survey responses are short, this serves as a coarse measure. Perhaps, future researchers can use this method on longer texts from blogs or on product review websites.

Clearly, the rich transaction dataset provided in-depth insights into understanding consumers' new role of micro-entrepreneurs and their distinctive behavioral patterns. Yet, new

questions continue to arise and an examination of all potential factors is beyond the scope of the current work. We open these interesting additional research questions to both the field of consumer behavior and marketing science and look forward to seeing fruitful future research within this intersection.

CHAPTER 5

CONCLUSION

The number of owned goods per household now exceeds over 300,000 items (MacVean 2014). The meanings and purposes of product ownership go beyond functional benefits and assistances, and extend to symbolic meanings. Possessions help individuals connect with the past, and present a tool to achieve their desired selves in the future. While there has been a burgeoning amount of research on product symbolism, not much research has fully examined the downstream consequences of such ownership, nor has it considered situations that lead people to "share" their possessed goods.

In an attempt to address this gap, my dissertation examined the implications of ownership (Essay 1) and the sharing of possessions (Essay 2). Specifically, Essay 1 shows the trade-off that consumers make when product ownership is salient in one's mind. I demonstrate that salient ownership activates the product-related self, but also deactivates other product-unrelated selves. The simultaneous identity activation and deactivation reveals that there is a finite limit. This puts forth the latent assumption in the literature that an individual can hold an infinite number of self-identities. Essay 2 focuses the topic of sharing, where people share their owned possessions with others. Unlike firms that are purely driven by financial revenue, consumers were found to have a diverse set of motivations behind sharing their possessions. Interestingly, a significant proportion of consumers were driven by non-cash motivation, which is different from the traditional economy. Importantly, the second essay also addresses the gap in consumer behavior research that is primarily dominated by lab experiments. By employing multi-methodological tools such as text-mining and the BG/BB retention model, I not only extract latent consumer motivation, but also show the downstream engagement pattern that is unique to each motivation group. This

advances the prior paradigm of consumer behavior research by proposing flexible tools for researchers.

Several streams of research deserve future attention. First, it would be interesting to understand factors that magnify this trade-off within the dynamic nature of identity. For example, is the see-sawing effect more pronounced among a conflicting pair of identities (athlete identity vs. math identity) than a pair of unrelated identities (cooking identity vs. math identity)? Is identity (de)activation more pronounced for self-aspects that compose a core (vs. peripheral) self? What are easy hands-on methods to measure identity (de)activation which happens without one's own awareness? How do unwanted self-identity (e.g., being an orphan) and a person's struggle to remove that identity play a role? Does adopting a new desired identity help? From a very young age, children acquire new identities and as people age, they discard old identities. Then are the old identities suppressed under the radar of awareness, or are they truly shed from one's self-identity?

A number of questions also arise on the topic of sharing. If possessions are an extension of the self, how does sharing affect one's reformation of self-identity? For example, does sharing my bike with a stranger affect whether I view myself more or less as a professional biker? If non-monetary reasons drive people's sharing behavior, what are the dynamics behind these non-monetary reasons? For example, an individual may be initially motivated to meet others, but later get fed up with the interactions, which then makes him/herself switch motivation. Or does successful sharing make amateur consumers turn into professional merchandisers? What is the right price point to compete with the traditional market?

Together, I expect a number of interesting research questions to be explored in the future. I believe that possessions are intimately interwoven to consumers' self-identity and the meanings

imposed on products comprise a significant portion of one's self-identity. The results and

discussion together suggest the importance of understanding consumer identity, and I look

forward to contributing on this topic of interest.

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APPENDICES

Appendix 1
Ikea catalogue (Experiment 1A, 1C)

Brochure 2-A	Brochure 2-D
HEMNES Mirror	ÄRSTID Wall lamp
Brochure 2-B	Brochure 2-E
KNARRA Basket	AINA Curtains, 1 pair
Brochure 2-C	Brochure 2-F
BEKVÄM Stepladder, 3 steps	SOCKERÄRT Vase

Appendix 2

Pantry Item Shopping Task (Experiment 1B, 1C)

1.

Toothpaste

$6.99 (for 3 toothpastes) $4.25 (for 2 toothpastes)

○   ○

2.

Toilet Tissue

$20.84 (for 40 rolls) $6.99 (for 12 rolls)

○   ○

Appendix 3

Follow-up Experiment 1

Methods

Pretest: Ownership manipulation. To test the ownership manipulation, forty MTurk participants were assigned to either the calculator ownership or the baseline condition. In both conditions, participants were asked to spend at least 3 minutes to describe how they would locate a calculator program on a computer desktop. The only difference between the two conditions was that participants described the location of the calculator program on their personal computer (ownership condition), or on a typical public library computer (baseline condition). After the task, we asked: "To what extent do you believe that your math skill-set is part of your own self?" (1: not part-of-my-own self, 7: part-of-my-own-self) (Weiss and Johar 2013, 2016). As expected, participants in the ownership (vs. baseline) condition believed that the math skill-set was an important part-of-the-self ($M_{ownership}$ = 5.52 vs. $M_{baseline}$ = 4.42; $F(1, 38)$ = 4.12, p = .049). The amount of time participants spent on the manipulation task did not differ ($F < 1$), and their perception of the quality of the described calculator did not significantly differ ($F < 1$). Procedure for the main experiment. Ninety MTurk participants first engaged in the same "computer software" study described above. In the second ostensibly unrelated task, all participants responded to a "sentence completion task" where they had to fill in 20 sentences beginning with the stem, "I am good at _____." This 20-statement task (Kuhn and McPartland 1954; Weiss and Johar 2016) was used to measure the activation of different identities. Upon completing the sentence completion task, they were shown their 20 statements and were asked to

code whether each skill set was related to the math skill set or non-math skill set. The proportion of math-related sentences served as our dependent variable.

Results and Discussion

As expected, participants in the ownership condition generated a greater proportion of math-related skills ($M_{ownership}$ = 27.68%, SD = .27) than participants in the baseline condition ($M_{baseline}$ = 18.42%, SD = .13; $F(1, 88)$ = 4.38, p = .039, d = .41). Thus, feelings of ownership over a calculator lead to greater activation of math identity and inversely, lower activation of other math-unrelated identities.

Follow-up Experiment II

If participants' feelings of ownership over a calculator activate their math identity, they should be better at accessing product-related content (e.g., math content) compared to those whose feelings of calculator ownership are not made salient.

Methods

MTurk participants (N = 55) completed the identical ownership manipulation (personal vs. public library computer) described above. Next, they engaged in a word completion task that is commonly used to measure implicit content accessibility in the self-identity literature (Johnson and Lord 2010; Knowles and Gardner 2008; Vargas, Sekaquaptewa, and von Hippel 2007). Specifically, we asked participants to complete 10 word fragments (e.g., ze[ro/st], div[ide/ine], nu[mber/gget], pl[us/an], min[us/ce]) as quickly as possible. For example, upon seeing "ZE_ _",

participants would fill in the blank to create a meaningful word, and could complete it as "ZERO"(math-related) or "ZEST" (math-unrelated). The amount of time participants spent on the task did not differ across the conditions ($F < 1$). The number of math-related words that participants generated served as a dependent variable.

Results and Discussion

As expected, participants in the ownership condition generated more math-related words than those in the baseline condition ($M_{ownership} = 5.37$, $SD = 1.81$ vs. $M_{baseline} = 4.36$, $SD = 1.70$; $F(1, 53) = 6.76$, $p = .012$, $d = .58$), suggesting that ownership salience of a calculator activated participants' math identity.

Follow-up Experiment III

This experiment demonstrates that in addition to activating product-related identity, salience of product ownership simultaneously deactivates product-unrelated identity.

Methods

The study employed a 2 (ownership: ownership vs. baseline) × 2 (math identity vs. art identity) between-subjects design. First, participants ($N = 197$) engaged in a "computer software" study, manipulating calculator ownership as in the previous experiments. In the second supposedly unrelated "Response Task," participants were asked to list reasons why it was important for them to be good at math (vs. art; between-subjects), and were given 45 seconds to

come up with as many self-identity associations as possible. This method has been successfully

used in prior literature to examine accessibility of different identities in one's mind (Chugani,

Irwin, and Redden 2015). The number of reasons served as a measure of accessibility of math-

and art-related identity.

Results and Discussion

As expected, participants in the ownership (vs. baseline) condition generated fewer

reasons for why art was important to them, suggesting relative deactivation of the art identity

($M_{ownership}$ = 4.06, SD = 1.79 vs. $M_{baseline}$ = 4.78, SD = 1.37; $F(1, 193)$ = 4.63, p = .033, d = .45).

In contrast, participants in the ownership (vs. baseline) condition generated more reasons why

math was important to them, suggesting relative activation of the math identity ($M_{ownership}$ = 4.88,

SD = 1.79 vs. $M_{baseline}$ = 4.14, SD = 1.65; $F(1, 193)$ = 6.23, p = .013, d = .43). Additional analysis

revealed that participants within the ownership condition generated significantly more reasons

for why math (vs. art) identity was important to them (p = .029). In contrast, participants within

the baseline condition generated marginally more reasons for why art (vs. math) was important

to them (p = .063).

Appendix 4

Quiz Content (Experiment 3, 4)

1. Select a figure from the four alternatives that would complete the figure matrix.
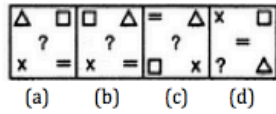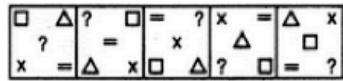
(a)   (b)   (c)   (d)

○ (a)

○ (b)

○ (c)

○ (d)

Appendix 5

Follow-up Experiment: Self-Concept Clarity (Individual Differences)

Measuring Self-concept Clarity

We used earphones as the stimulus product category and performance on an anagram task as the dependent variable. By using music-related words for the anagram task, the task can plausibly be labeled as measuring people's music comprehension skills (earphones product-related task) or creative writing skills (earphones product-unrelated task). We used a different ownership manipulation in this study.

Ninety-two MTurk participants (50.0% male, $M_{age} = 33.45$, SD = 10.07) were randomly assigned to either the ownership or the baseline condition. Participants in the ownership condition described what earphones/headphones (hereafter, earphones) they owned and their usage experience with their earphones while those in the baseline condition described how they used a notepad to keep track of things in life and the kinds of things (e.g., grocery list) that they wrote down on their notepad. All participants were asked to spend a minimum of 3 minutes on the task. To verify that the earphones ownership manipulation activated music identity, participants responded to a Part-of-Self question on their music comprehension skills. As expected, participants in the ownership condition perceived music comprehension skills as being more a part of their self compared to those in the baseline condition (POS score: $M_{ownership} = 4.83$ vs. $M_{baseline} = 4.02$; $F(1, 120) = 36$, $p = .040$).

As desired, music comprehension skills and creative writing skills were perceived to be unrelated (N = 50; M = 1.19 on a -10 to 10 point scale) and moderately important ($M_{music\text{-}comprehension} = 4.23$, $M_{creative\text{-}writing} = 5.06$ in a 1 to 10 point-scale).

Methods

A total of 194 MTurk participants (44.0% male, M_{age} = 35.42, SD = 11.42) were randomly assigned to one of the conditions in a 2 (ownership: ownership vs. baseline) × 2 (quiz label relevance: related vs. unrelated) between-subjects design and self-concept clarity was measured as a third factor. Participants either described their earphones (ownership condition) or a notepad (baseline condition) for at least three minutes. Next, in an ostensibly unrelated second study, participants were randomly assigned to either the music comprehension assessment or the creative writing skills assessment task. The tasks were identical and only the task label differed between conditions. After reading the instructions, all participants solved the same ten anagram questions (e.g., score, octave, tune) that could be perceived as measuring creative writing or music comprehension. Each anagram was shown on the screen separately, and participants moved on to the next screen at their own pace. After responding to the anagram questions, participants rated their levels of effort and involvement and the perceived difficulty of the quiz. Finally, all participants responded to a few filler questions, followed by the self-concept clarity measure (Campbell et al. 1996), some demographics and debriefing questions

Results and Discussion

There were no significant differences in participants' self-reported levels of effort, involvement and perceived quiz difficulty. Participants were generally engaged in the task (M_{effort} = 6.31; $M_{involvement}$ = 6.30 on a 7-point scale). The anagram task was perceived as moderately difficult ($M_{difficult}$ = 5.09 on a 7-point scale). Overall, these results demonstrate that

participants' performance was not consciously driven by the goal of doing worse on a product-unrelated (vs. product-related) task.

Quiz performance. We expected to replicate previous results for participants who have a less clear self-concept such that they perform worse on a task labeled as product-unrelated (vs. product-related). We expected the effect to be attenuated among participants who had a clear, well-defined self-concept. The mean self-concept clarity score was 3.62 (SD = 1.00). We followed the guidelines of Spiller et al (Spiller et al. 2013) for the analysis. First, we ran a regression analysis using ownership (-1 = baseline, 1 = ownership), quiz (-1 = product-unrelated label, 1 = product-related label), self-concept clarity and their two-way interactions and three-way interactions as predictors and the anagram score as the dependent variable. Results revealed a significant three-way interaction of ownership × quiz × self-concept clarity (β = -.63, t(186) = -2.29, p = .023), and a significant 2-way interaction of ownership × quiz (β = .69, t(186) = 2.52, p = .013). Floodlight analysis revealed that the ownership by quiz interaction was significant among participants with self-concept clarity score below 3.18, but not those with a score higher than 3.18 (Bjn = .26, SE = .13, p = 0.05).

Next, we conducted spotlight analysis to examine score differences between the 4 conditions under a low vs. high self-concept clarity score. Consistent with H2, there was a significant 2-way ownership × quiz interaction at 1 SD below the mean of self-concept clarity (t(186) = 2.42, p = .017), but not at 1 SD above the mean of self-concept clarity (t(186) < 1). At 1 SD below the mean of self-concept clarity, simple effect analysis supported H1b and revealed that within the creative writing quiz condition, participants in the earphones ownership condition performed significantly worse than those in the baseline condition, (β = -1.12, t(186) = -2.22, p = .028, d = .57). Within the music comprehension quiz, the difference between the earphones

ownership and the baseline condition was not significant, despite the pattern being consistent with H1a (β = .53, t(186) = 1.15, *p* = .257, d =.30).

Additional analysis also revealed that participants in the earphones ownership condition performed worse on a creative writing quiz (product-unrelated label condition) than on a music comprehension quiz (product-unrelated label condition) (β = 1.17, t(186) = 2.23, *p* = .027, d = .58). There were no differences between the scores within the baseline condition (β = -.48, t(186) = -1.10, *p* = .28, d = .28). The correlation between self-concept clarity and age was small (r = .133).

Appendix 6

List of Companies Interviewed

Company Interviews	We interviewed executives from 8 companies to understand the importance of consumer performance in relation to their business. The names of these executives are kept anonymous. These companies were: Education industry EdX Coursera Samberg Institute (Columbia University) Books that Grow Cengage Gaming Industry Lumos Lab Wooga King Games
Additional Data Analysis	Data from online executive program additionally revealed a positive relationship between engagement (e.g., greater time spent on online courses) and the likelihood of class recommendation to others, knowledge application and overall satisfaction, thereby emphasizing the importance of understanding consumer performance in relation to the success of the company.

Appendix 7

Idiographic Rank Experiment

This follow-up experiment uses an idiographic approach to examine the scope of deactivation based on individual perceptions of correlation between different identities. Results can address the question of which identities are deactivated when a single identity is activated.

Method

The experiment was run in two parts. The first part was conducted one week prior to the main experiment and measured each participant's chronic activation level of five target identities. Specifically, fifty-two MTurk participants ranked a list of five identities (identity related to math, art, music, being an athlete, being a writer) in the order of importance to them. These five identities were chosen because these identities are associated with basic disciplines in most primary and secondary U.S schools. Next, participants responded to Part-of-self (POS) questions (Weiss and Johar 2013, 2016) for each of the five identities: "To what extent do you believe that each of these identities are an important part of your own self?" (1: not part-of-my-own-self, 7: part-of-my-own-self). These POS ratings served as baseline measures of identity activation.

One week later, participants completed the second part of the study. The goal of this study was to examine changes in participants' POS scores for each of the five identities (one of which was activated via an ownership manipulation), compared to their respective baselines from a week ago. For each participant, we manipulated their feelings of ownership over a product that they had personally ranked as being moderately important (i.e., 3rd of five ranked

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identities) on the first survey. For instance, an individual who ranked an athletic-identity as third in terms of importance, was asked to describe an athletic product that s/he owned. Each participant engaged in the owned product description task related to the identity that they had ranked third. After the description task, all participants responded to the identincal Part-of-self (POS) questions as those from a week ago. Finally, participants rated their perceptions of how the five identity skill sets were correlated with each other. All five identities were paired with each other, resulting in ten pairs of correlation questions in total.

Results and Discussion

We predicted that the POS score would increase for the activated identity (i.e., the 3rd ranked identity), whereas the POS scores would generally decrease for the remaining 4 identities that were not activated (especially if they were negatively correlated or unrelated to the activated identity). To test this idea, we first calculated the POS_{change} score ($POS_{after} - POS_{before}$) for the activated identity, and then compared the score with the average of the four other POS_{change} scores (e.g., "$POS_{change\ for\ athletic\ identity}$" vs. "average $POS_{change\ for\ other\ 4\ identities}$"). As expected, a paired t-test revealed that the 4 identities were relatively deactivated compared to the activated 3rd ranked identity ($M_{pos\ change\ for\ the\ activated\ identity}$ = .54 vs. $M_{pos\ average\ change\ for\ 4\ identities}$ = -.21; $t(51)$ = -3.00, p = .004). Additional analysis revealed that the POS change for the activated identity ($M_{pos\ change\ for\ the\ activated\ identity}$ = .54) was also significantly greater than zero ($t(51)$ = 2.05, p = .045). The average POS change for the four other identities ($M_{average\ pos\ change\ for\ 4\ identities}$ = -.21) was not significantly different from zero ($t(51)$ = -1.59, p = .120). This average change score masks potential deactivation (i.e., a negative change score significantly below zero) because some of the four identities are positively correlated with the target activated identity and hence, not

expected to show deactivation. We therefore examined deactivation of each of the four identities separately based on their individual-level correlations with the activated identity.

Identities that are positively correlated with the activated identity are less likely to be deactivated whereas identities that are negatively correlated with the activated identity, or unrelated to the activated identity, are more likely to be deactivated. To test this proposition, we first examined the distribution of correlation scores between the activated identity and the other 4 identities across all participants. Fifty-one percent of correlation scores were between -10 to 1 and 49% were between 2 and 10. We expected evidence for deactivation for the identities that were negatively correlated or unrelated with the target identity. Paired t-tests revealed that the $POS_{\text{change of identities with correlation -10 to 1}}$ (M = - .38) was significantly lower than the $POS_{\text{change of activated identity}}$ (M = .49; t(48), p = .003[11]). This score was also significantly below zero (t(48) = -2.28, p = .027). For identities with correlation 2 or higher, the $POS_{\text{change of identities with correlation 2 to 10}}$ (M = -.21) was also significantly lower than $POS_{\text{change of activated identity}}$ (M = .51; t(42) = -2.53, p = .015), suggesting relative deactivation compared to the target identity, but this score (M = -.21) was not significantly different from zero (t(42) = -1.14, p = .262).

These results reveal that identity activation leads to relative deactivation of other identities. The degree of deactivation is greater for identities that are unrelated and negatively related to the activated identity. However, the limitation of this study is that the effect seems to vary by where the cut-line is for negatively related vs. unrelated vs. positive related identities. Future research can investigate this idea further.

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[11] Note the different total N and means for the activated identity from the initial analysis. This is due to the fact we had to exclude participants who indicated that their activated identities and the remaining four identities were all positively correlated (i.e., correlation score of 2 or higher).

Appendix 8

The Comparison of the Current Data and the Control Data

	Current Data	Control Data
North America	58.58%	55.22%
Latin America	3.24%	3.50%
Europe	24.93%	29.20%
Australia	9.04%	7.81%
Asia	2.84%	3.29%
Africa and Middle East	1.21%	0.93%
-unknown-	0.15%	0.05%
Entire home/apt	60.36%	64.50%
Private Room	38.42%	34.47%
Shared Room	1.21%	1.03%
Others	0.08%	0.00%
Number of Words used to Describe a Property	362.88	362.6
Booking Overall Ratings	4.71	4.65
Number of Amenities at a Property	11.59	12.65
Number of Nights Open for Booking per Year	177.44	178.7
Number of Reservations	33.75	40.2
The Count of Reviews Received	21.35	24.21
Host Age	42.82	40.72
Number of Photos Uploaded	16.64	17.29

Note -. This table compares the transaction dataset of hosts who responded to the open-ended survey, with the control dataset that is composed of hosts who did not respond to the survey. The comparison result reveals that the host traits are approximately similar with each other, suggesting that our transaction dataset is not suffering from the self-selection bias.

Appendix 9

Receiver Operating Characteristic Graph
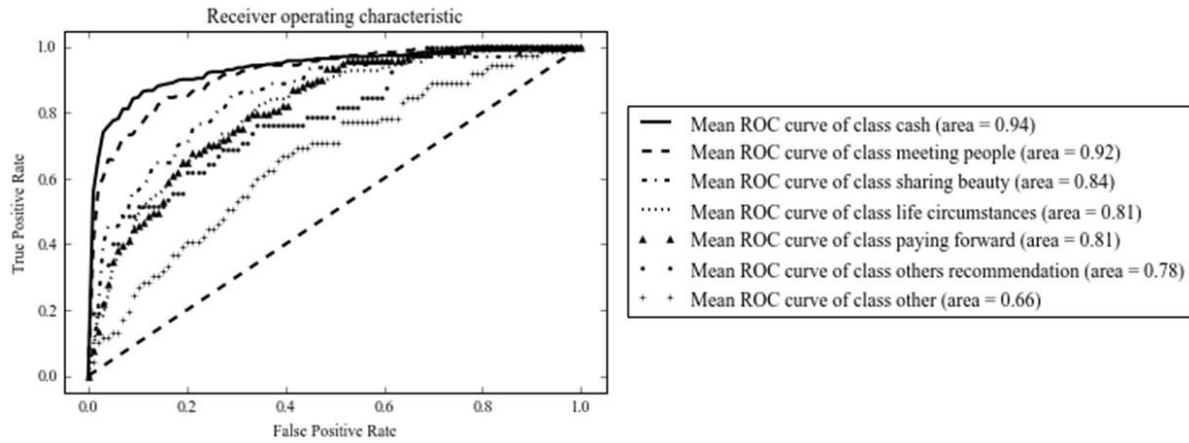
Note -. In statistics, receiver operating characteristic (ROC), or ROC curve, is a graphical plot that illustrates the performance of a binary classifier when discrimination threshold is varied.

Appendix 10

Text Data Preprocessing

We pre-processed the textual data by following standard pre-processing practice in text-mining (Moe, Netzer, and Schweidel 2017) using the following steps: 1) we first tokenized text - a process that breaks down each survey response into a stream of distinct words, 2) we corrected spelling mistakes (using "autocorrect" package in Python), and replaced special characters with English words if the characters conveyed meaningful information (e.g., "$" to "cash"); 3) we changed all letters into lower case, and removed numbers and symbols, and 4) eliminated non-English words and stop words that are defined by a list of commonly used words in English (e.g., "a", "the", "this" using the NLTK package in Python). A set of less relevant words that frequently appear in our textual data were removed manually.[12] In total, this procedure resulted in over 340,000 tokens, corresponding to 12,157 unique words. We then created a vocabulary of words that appeared at least twice in the corpora. Our final vocabulary contains 6,861 unique words.

Then, we used term frequency-inverse document frequency (tf-idf; (Salton and Buckley 1988) as model inputs Tf-idf measures the weighted occurrence of a word by comparing the frequency of the word and the length of the textual response. For instance, if the word, "vacation" appears 7 times in a host's response (high tf), but the same word also appears frequently across all the other host responses in the dataset, the word "vacation" is penalized

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[12] Our stop words list consists of 40 very common words (e.g. "Airbnb", "air", "bnb", "even","really","re","ve",'still','much','could','would',…) and abbreviations of months (e.g. "jan", "feb",…).

(high idf) due to the word's lack of uniqueness in delivering meaningful information about the

particular host.

Appendix 11

The Proportion of Motivation Co-occurrence Based on Human-coded Text Data

Meet people   Share beauty

13.18%   7.03%   5.47%

5.86%

Other motivations

12.70%   4.88%   16.02%

34.77%
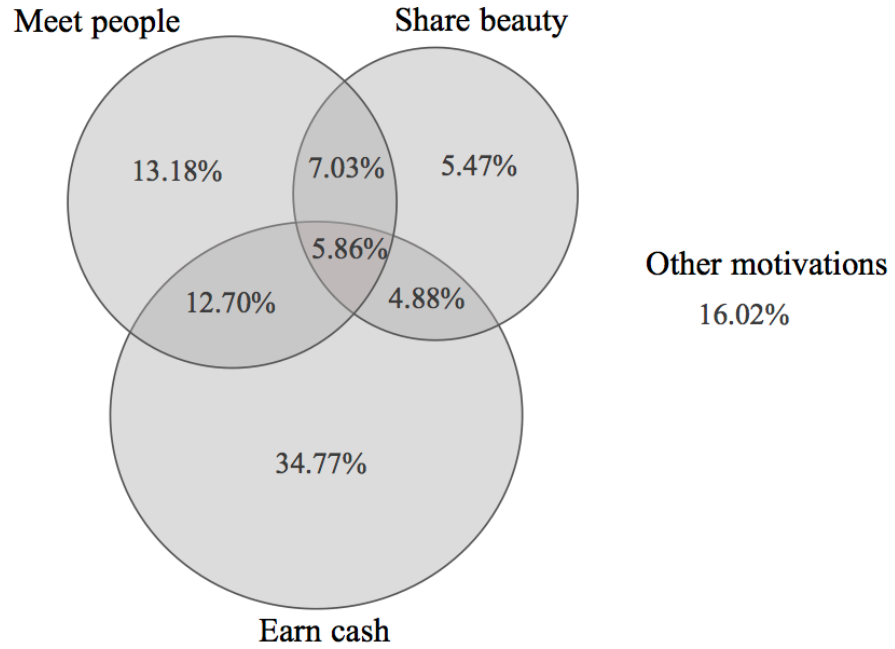
Earn cash

Appendix 12

Full Table with the Combinations of Different Motivations

Motivations	Number of Words used to Describe a Property	Number of Photos	Nights Active per Year
Earn Cash	339.38	15.77	160.25
Meet People	379.33	16.55	193.60
Share Beauty	379.74	17.49	180.65
Earn Cash & Meet People	369.48	15.66	182.40
Earn Cash & Share Beauty	376.99	17.48	181.75
Meet People & Share Beauty	410.06	17.61	197.33
Earn Cash & Meet People & Share Beauty	422.52	17.12	193.14

Appendix 12

Property Traits by Motivation Type (Based on Multi-label Classification)

	Listing Person Capacity	Listing Bedroom	Listing Number of Facilities	Listing Room Type		
				Entire Home	Private Room	Shared Room
Earn Cash	3.35	1.43	11.33	70.07%	29.00%	.94%
Meet People	3.06	1.31	11.76	39.58%	58.45%	1.97%
Share Beauty	3.98	1.61	11.80	71.78%	27.32%	.89%

Appendix 14

Appendix 14A

Host Engagement Regression Results when Controlling for Property Traits

	listing # of photos		# of words used in ad description		listing total nights active per year	
	Estimate		Estimate		Estimate	
(Intercept)	4.228		-233.200		-80.213	
earn cash	-0.042		-1.245		-5.065	***
share beauty	0.518	**	23.150	***	-0.007	
meet people	0.696	***	22.000	***	6.956	***
host is verified	1.405	***	45.490	***	36.146	***
host has profile photo	1.533	***	34.820	***	81.875	***
hosts' total booking as guest	0.083	***	2.512	***	0.579	***
listing person capacity	0.519	***	6.807	***	1.432	**
instant booking available	2.881	***	46.370	***	39.647	***
contact interaction	0.038	**	1.695	***	-1.245	***
average reservation guests	0.588	***	-0.545		4.498	***
long-term rent available	1.660	***	37.190	***	47.488	***
cable	0.943	***	-12.690	***	9.553	***
wireless internet	0.743	**	8.010		-10.522	***
ac	-0.371	*	-14.910	***	-6.624	***
_pool	1.458	***	11.880	*	5.831	**
kitchen	0.187		-4.520		-20.972	***
free_parking	0.216		9.462	*	10.372	***
allows_smoking	1.842	***	7.907		-1.510	
allows_pets	-0.034		-0.421		-0.458	
laundry	0.655		-115.200	***	44.588	***
doorman	0.623	*	-10.380		0.806	
_gym	-0.287		15.530	*	-19.715	***
breakfast	0.984	***	35.540	***	11.964	***
elevator	-0.299		-16.790	**	-6.834	***
jacuzzi	0.829	***	-8.660		3.164	
fireplace	0.997	***	4.118		6.433	***
buzzer	0.653	***	23.200	***	-3.936	*
heating	-0.874	***	14.880	**	4.659	*
family_friendly	0.685	***	16.320	***	4.249	**

event_friendly	1.676	***	17.380	**	1.646	
washing	1.001	***	5.184		-2.354	
dryer	-0.769	***	-2.004		-13.512	***
essentials	1.607	***	57.370	***	39.203	***
shampoo	1.085	***	39.740	***	24.343	***
pets	0.873	***	42.730	***	11.113	***
local market price in the same region	-0.011	***	0.047		-0.176	***
room_typeEntire home/apt	-0.631		72.220		88.820	
room_typeEntire home/flat	-5.756		283.400		-36.104	
room_typePrivate room	-3.112		79.530		74.238	
room_typeShared room	-5.529		79.310		44.922	
cancellation_policyflexible	-2.153		111.100		93.907	
cancellation_policymoderate	0.118		178.500		107.482	
cancellation_policyno_refunds	-3.753		115.500		66.201	
cancellation_policystrict	1.529		213.100		121.032	
cancellation_policysuper_strict_30	-1.711		307.300		103.005	
average number of reserved nights	-0.052	***	-1.476	***	-1.334	***
overall star rating	1.577	***	14.740	.	-3.698	
accuracy star rating	1.216	***	5.690		-1.930	
cleanless star rating	0.834	***	10.840	.	12.414	***
communications star rating	-0.517		12.070		-11.805	***
checkin star rating	-0.423		10.870		5.366	.
value star rating	-0.624	*	-0.004		-0.125	
location rating	-0.803		-22.370	***	2.210	

Note -. The results are based on regression analyses. Each of the individual hosts had the 3 main motivations dummy coded as 0 or 1. Variables 1-6, 9, 12-36, 38-46 were dummy coded. The remaining variables are continuous variables. Comparing coefficients h of the 3 motivations reveal that sharing beauty and meet people motivations lead to greater engagement (positive coefficients) than the motivation to earn cash (negative coefficient).

Appendix 14B

Regression of Motivations on Property Characteristics

	Earn Cash		Meeting People		Sharing Beauty	
	Estimate		Estimate		Estimate	
(Intercept)	-0.2915		-1.254	***	-1.6014	***
host is verified	0.1165	.	-0.0459		-0.0452	
host has profile photo	-0.1445	*	0.2073	**	0.126	.
listing person capacity	-0.0425	*	-0.0472	*	0.0236	
listing number descriptive words	0.0001		0.0005	***	0.0006	***
listing number of photos	-0.0116	**	0.0095	*	0.0059	
Listing number of professional photos	0.0126	**	-0.0033		-0.0049	
listing_room_type_private	-0.0822		0.9411	***	0.0717	
listing_room_type_shareroom	-0.239		0.9653	***	0.1148	
listing_cancellation_policy.moderate	-0.0492		-0.071		-0.0334	
listing_cancellation_policy.strict	-0.1056		-0.0484		0.0362	
avg_listing_is_instant_bookable	-0.2291	*	0.146		0.0745	
cable	0.0659		0.0115		-0.1595	*
wireless_internet	0.2495	*	-0.0712		-0.0924	
ac	0.1666	**	0.0433		0.0853	
pool	0.113		0.0773		-0.0111	
kitchen	0.2176	*	-0.0331		0.0093	
free_parking	-0.2244	***	0.1381	*	0.178	*
allows_smoking	0.0475		0.1615		0.0176	
allows_pets	-0.0319		0.0033		-0.001	
doorman	-0.1712		-0.0555		0.0663	
gym	0.1343		-0.0472		-0.2033	
breakfast	-0.2229	**	0.3088	***	0.3158	***
elevator	0.0805		0.0186		-0.0659	
jacuzzi	-0.1273		-0.2237	*	-0.0076	
fireplace	-0.0203		-0.0982		0.0854	
buzzer	0.1106		-0.1875	*	-0.0894	
heating	0.204	*	-0.1193		-0.0522	
family_friendly	0.0211		-0.0188		-0.0068	
event_friendly	-0.0826		0.2264	*	0.0036	

washing	-0.1291	0.0412	-0.2322	*
dryer	0.1069	-0.075	0.1712	.
essentials	0.0741	-0.1422 .	0.0272	
shampoo	0.0371	0.2532 ***	0.0107	
pets	0.092	0.1403		

Signif. Codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

Appendix 15

Compiled Results of Poisson Factorization Analysis

Appendix 15A

The Convergence of the Poisson Factorization

Motivation	Poisson Factorization					
	Correlation with multi-label classification	Correlation with human coding	Hit-rate	Jaccard index	Average of posterior probability	
					Human coding = 1	Human coding = 0
Cash	0.51	0.52	72%	0.55	0.58	0.08
Meet People	0.59	0.61	80%	0.57	0.7	0.14
Share Beauty	0.51	0.5	83%	0.44	0.66	0.13

Note –. The "Correlation with human coding" column shows the correlation between Poisson Factorization and multi-label classification motivation factors. The remaining columns compare the Poisson Factorization results with that of human coding. Poisson analysis does not require human-coding. Yet, a comparison with the human coded dataset provides evidence that the analysis is reliable. The average posterior probability columns report the average of Poisson Factorization posterior probability for hosts who have been coded as 1 (or 0) by Mturkers.

Comparing the Two Motivation Extraction Approaches

Overall, the motivations to "Earn cash", "Meet people" and "Share beauty" are uncovered by both the multi-label classification and Poisson Factorization analysis. The other motivation factors did not match across the two analyses casting doubt on their robustness.

To further ensure the convergent validity of both analyses for the three motivations, we examined the correlations between the results of Poisson Factorization and the multi-label classification. Both approaches identified the three motivations in the text with high correlation: R_{cash} = .51, $R_{meeting\ people}$ = .59 and $R_{sharing\ beauty}$ = .51. Next, assuming that human-coded data can serve as a gold-standard for the true motivation expressed in the text (Liu et al. 2012; Shiyan Ou, Khoo, and Goh 2008), we examined the performance of Poisson Factorization in capturing the motivations in the text. The correlations between the Poisson Factorization results and the human coded data were also high (Cash = .52, Meeting people = .61 and sharing beauty = .50). Next, we convert the Poisson Factorization probability of each motivation into a binary variable based on the mean of each motivation, so that we can examine the hit-rate and Jaccard index by comparing the Poisson Factorization results and the human-coded data. Results revealed that all hit-rates were above 67% suggesting that the Poisson Factorization can capture whether a topic was mentioned versus not in each text. Finally, we also examined the probability of the motivation in the Poisson Factorization when the motivation was identified in the text by the human coder. This number was always significantly higher compared to when the motivation was not identified in the text by the human coders (based on a paired t-test), suggesting that our analysis is reliable.

Appendix 15B

Model-Free Evidence of Host Behavior by Motivation (Poisson Factorization)

Motivations	Number of Words used to Describe a Property	Number of Photos	Nights Active per Year
Earn Cash	332.57	14.20	162.04
Meet People	381.65	16.41	185.96
Share Beauty	357.83	16.96	177.53
Earn Cash & Meet People	371.15	15.96	185.63
Earn Cash & Share Beauty	349.69	16.19	170.80
Meet People & Share Beauty	413.50	18.07	199.29
Earn Cash & Meet People & Share Beauty	415.52	17.68	200.06

Appendix 15C

Retention Model using Poisson Factorization

	Listing Person Capacity	Listing Bedroom	Listing Number of Facilities	Listing Room Type		
				Entire Home	Private Room	Shared Room
Earn Cash	3.35	1.43	11.33	70.07%	29.00%	.94%
Meet People	3.06	1.31	11.76	39.58%	58.45%	1.97%
Share Beauty	3.98	1.61	11.80	71.78%	27.32%	.89%

The strength and the direction of the coefficients were similar with those from the multi-label classification output. The WAIC is 77478.29, which is also close to that of the multi-label classification reported in the main text, suggesting that both models outperform the baseline model.

Expected CLV simulation process

Input:
        I: number of hosts in BTYD model (5000)
        M: number of draws from posterior distribution (1000)
        T: number of months for simulation (18, 36, 1200)
        δ: discount factor (0.99) per period (month)

Output:
        d_{im} : draw m of alive months of host i
        y_{imt}: draw m of open (or not) month made by host i at period t
        Y_{im}: draw m of total open months made by host i

Simulation steps:

$y_{imt}=0$, $d_{im}=0$

for m in 1:M do

    for i in 1:I do

$$d_{im} \sim Geometric\ (\ logit^{-1}\left(\widehat{\alpha_{im}^{\theta}} + \widehat{\beta_{im}^{\theta}}\ x_{it}\right))$$

        If $d_{im} > 0$

            for t in $1 : \min(d_{im}$, T)

                $u \sim U[0,1]$

$$p_{imt} \sim\ logit^{-1}\left(\widehat{\alpha_{im}^{P}} + \widehat{\beta_{im}^{P}}\ x_{it}\right)$$

$$y_{imt} = 1(u \le p_{itm})$$

        End

$$Y_{im} = \sum_{t=1}^{T} \delta^t * y_{imt}$$

        End

    End

End

Expected CLV per motivation (Poisson Factorization)

	Baseline	Cash	Meeting people	Sharing beauty
Churn Rate	2.44%	2.84%	1.97%	1.70%
Open Rate	83.41%	84.11%	82.80%	82.74%
# of Months Alive	23.74	23.29	26.04	27.04
# of Months Open	14.85	14.57	15.95	16.61
Expected CLV with Motivation ($)	15,080	12,780	13,660	16,070

Appendix 15E

Price Decision using Poisson Factorization

Average Price per Night (US $) by Motivations

	Poisson
Earn Cash	144.22
Meet People	156.97
Sharing Beauty	156.97

Appendix 16

## Regression Results when Controlling for Property Traits

DV: Price per Night

	Multi-Classifier		Poisson Factorization	
	Estimate		Estimate	
(Intercept)	-2.27E+02	*	-2.28E+02	*
earn cash	-1.99E+00	.	-1.50E+00	
share beauty	1.71E+00		-3.21E+00	**
meet people	-4.01E+00	***	1.34E+00	
host is verified	2.88E+00	**	2.89E+00	**
host has profile photo	-5.05E+00	***	-5.04E+00	***
hosts' total booking as guest	-2.91E-01	*	-2.92E-01	*
listing person capacity	2.81E+00	***	2.84E+00	***
instant booking available	-7.58E+00	***	-7.54E+00	***
contact interaction	8.21E-01	***	8.27E-01	***
average reservation guests	3.73E+01	***	3.73E+01	***
long-term rent available	-8.43E+00	***	-8.51E+00	***
cable	9.26E+00	***	9.23E+00	***
wireless_internet	1.18E+01	***	1.19E+01	***
ac	7.48E+00	***	7.46E+00	***
pool	3.08E+00	.	3.16E+00	.
kitchen	-3.63E+00	.	-3.73E+00	*
free_parking	-5.76E+00	***	-5.70E+00	***
allows_smoking	-5.18E+00	**	-5.20E+00	**
allows_pets	-3.74E+00	**	-3.77E+00	**
laundry	-3.74E+00		-3.89E+00	
doorman	7.78E+00	***	7.74E+00	***
gym	2.44E+00		2.33E+00	
breakfast	2.65E+00	.	2.75E+00	*
elevator	4.40E+00	**	4.43E+00	**
jacuzzi	3.97E+00	*	3.96E+00	*
fireplace	7.85E+00	***	7.98E+00	***
buzzer	2.07E+00		2.09E+00	
heating	5.28E+00	***	5.21E+00	***
family_friendly	-1.02E+01	***	-1.02E+01	***
event_friendly	1.46E+01	***	1.46E+01	***

washing	-1.19E+00		-1.24E+00	
dryer	1.13E+01	***	1.13E+01	***
essentials	-5.96E+00	***	-5.97E+00	***
shampoo	6.28E+00	***	6.30E+00	***
pets	6.17E-01		6.48E-01	
local market price in the same region	8.18E-01	***	8.17E-01	***
room_typeEntire home/apt	-3.83E+01		-3.84E+01	
room_typeEntire home/flat	-1.52E+02		-1.50E+02	
room_typePrivate room	-1.49E+01		-1.53E+01	
room_typeShared room	-1.27E+01		-1.32E+01	
cancellation_policyflexible	5.69E+01		5.79E+01	
cancellation_policymoderate	5.86E+01		5.95E+01	
cancellation_policyno_refunds	7.48E+01		7.51E+01	
cancellation_policystrict	7.14E+01		7.23E+01	
cancellation_policysuper_strict_30	6.53E+01		t_30 6.771e+01	
average number of reserved nights	-1.09E+00	***	-1.08E+00	***
overall star rating	2.73E+01	***	2.72E+01	***
accuracy star rating	8.89E+00	***	8.80E+00	***
cleanless star rating	1.19E+01	***	1.20E+01	***
communications star rating	2.74E+00		2.71E+00	
checkin star rating	1.56E+00		1.57E+00	
value star rating	-5.90E+01	***	-5.89E+01	***
location rating	2.92E+01	***	2.93E+01	***
number of words used in the ad	-5.78E-03	**	-5.69E-03	**
listing number of photos	3.04E-01	***	3.05E-01	***
listing total nights active per year	-9.86E-03	.	-9.69E-03	.

Signif. codes: 0 '***' 0.001 '**' 0.01   '*' 0.05 '.' 0   .1 ' ' 1

Appendix 17

Experiment 1: Property Pictures
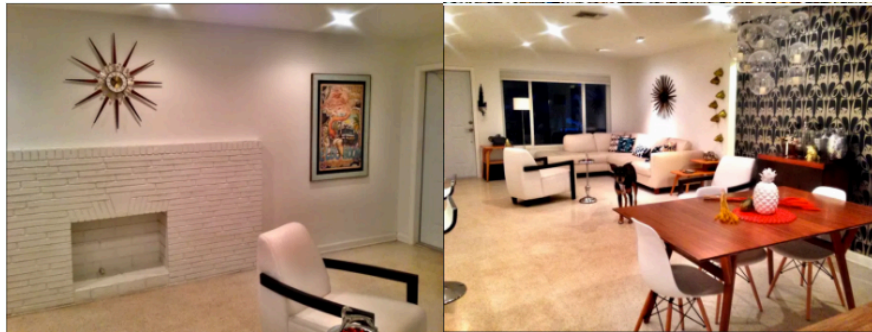
Appendix 18

Pretest for Experiment 1

Method. A total of 131 MTurk participants (Mage = 33.72, Male = 51.1%) were randomly assigned to one of the three conditions: Cash, Meet People, Share Beauty. Depending on the conditions, participants were given the following instruction.

Cash: The Airbnb platform provides you a chance to supplement your income and allows you to spend the earned money for other purposes. In what ways do you think the supplementary income from hosting can help you financially? You can describe where and how you would like to spend the extra income.

Meet People: The Airbnb platform allows you to make friends from around the world. You get to learn about their culture, their life story and about the country they live in. What do you think you would particularly enjoy as a host when meeting people from different regions? You can think of the social interactions with these guests and what you would talk about, and what you would do when you meet them.

Share beauty: The Airbnb platform gives you a chance to share your beautifully and uniquely decorated home. What aesthetic aspects would you like to emphasize when you are hosting guests? You can describe unique features, furniture and decorations, and any other aspects that can highlight the beauty of your property.

After engaging in one of the three writing tasks, all participants responded to 6 questions. Each of the two items measured how much participants were motivated for the target three motivation factors. Cash: (1) I primarily thought about the financial benefit when hosting through Airbnb. (2) I mainly thought about where and how I can use the extra income ($\alpha = .94$); Meet People: (1) I primarily thought of the enjoyment of meeting people from around the world, (2) I mainly thought about how I would enjoy meeting people and learning about them ($\alpha = .88$); Share Beauty: (1) I mostly focused on the aesthetic aspects of my home, (2) I mainly thought about how proud I am with this beautifully maintained home ($\alpha = .78$). Each of the two questions were averaged to composite the Cash-score, Meet-People-score and the Share-Beauty-score. All questions were anchored in a 7-point Likert point scale (1: not at all, 7: very much). Lastly, all participants reported their level of effort and involvement in the task.

Results. As expected, participants in the Cash condition scored higher than the other two groups in the Cash-score ($F(2, 128) = 35.96$, $p < .001$; $M_{cash} = 6.02$, $M_{meet-people} = 2.01$, $M_{share-beauty} = 1.95$). Participants in the Meet-People condition scored higher than the other two groups in the Meet-People-score ($F(2, 128) = 28.60$, $p < .001$; $M_{cash} = 3.01$, $M_{meet-people} = 5.27$, $M_{share-beauty} = 3.20$). Similarly, those in the Share-Beauty condition scored higher than the other two groups in the Share-Beauty-score ($F(2, 128) = 12.29$, $p < .001$; $M_{cash} = 4.05$, $M_{meet-people} = 3.72$, $M_{share-beauty} = 5.40$). Follow-up analyses that compared the scores for the two other groups in each of these three analyses revealed no significant differences between the two (all p's $> .13$). There were no significant differences on participants' level of effort ($F < 1$) and involvement ($F < 1$) in the manipulation task.

Appendix 19

Experiment 2: Property Pictures

Appendix 20

Experiment 2 Description of Different Motivations

We are interested in why you would post the private room in your home on the Airbnb

site. People join Airbnb as hosts for several reasons. Here are a few reasons why people post

their homes:

To share the beauty of their home: Hosts find pleasure in sharing a room in

their beautifully and authentically decorated home. These hosts find joy in sharing "what

is beautiful of their home." They like to share the authentic experiences of enjoying the

nicely maintained home with these guests.

To meet people from different regions/culture/countries: Hosts find pleasure in meeting

people from different cultures and backgrounds. These hosts find pleasure in social

interactions, learning new cultures, and making new friends when they rent out a room in

their home.

To earn cash: Hosts are mainly interested in earning cash by renting out a room in their

home. They find extra income helpful in supplementing their needs. To these hosts,

renting out their room is a useful mean to pursue their financial well-being in their lives.