

The Venmo Effect: The Impact of Digital Payment Platforms on Consumer Willingness to Pay

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April 28, 2021

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Submitted to the Department of Economics of Amherst College in partial fulfillment of the requirements for the degree of Bachelor of Arts with Honors

Abstract

Using data from an online purchasing experiment, we show that Venmo, a digital payment platform with over 40 million users, increases consumer willingness to pay (WTP). While the impact of credit cards on WTP has been documented, the role of Venmo has not previously been studied. We conduct an online RCT with undergraduate students in which participants are randomly assigned to a payment form of either Venmo, credit, or debit and then partake in ten Becker, DeGroot, and Marschak (1964) lotteries to estimate their WTP for ten low-cost consumer goods. Our main finding is that WTP with Venmo had the highest mean WTP (\$1.12; s.e. (\$0.037)), followed by debit (\$1.07; s.e. (\$0.058)), and then credit (\$0.96; s.e. (\$0.074)). Within Venmo, WTP is highest when using the *Public* setting of the Venmo app and lowest when using the *Friends Only* setting. Using the app's social feeds to view other users' transactions on the app does not increase WTP uniformly; rather, priming is found to amplify the existing effect of the user's privacy setting on WTP.

JEL classification: D12, D91, M310, Z13

Keywords: Behavioral, Mental Accounting, Preferences, Social Inclusion, Social Media, Willingness to Pay, Venmo

Acknowledgements

Professor Debnam – thank you for being the best thesis advisor I could have imagined. Even before I ever considered writing a thesis, your behavioral economics courses provided reassurance at a time when I was questioning the entire field of economics. I would have been lost this year without you.

Professor Baisa – thank you for assigning the microeconomics paper that inspired the *Venmo Effect*. I wouldn't have written a thesis without you. Thank you for being willing to help with literally anything throughout my Amherst career (but especially all my thesis questions).

Professor Theoharides – thank you for helping me feel confident in my ability to write a thesis, back in junior year when I wasn't sure if I could (or even wanted to).

Everyone who tested my survey – thank you for taking the time to be my guinea pigs. My experimental design was much stronger because of your feedback.

All the professors across New England who distributed my survey to their students – I quite literally could not have done this without you.

Gib – great minds think alike. Thank you for being a sounding board and taking the time to offer such insightful comments.

All my friends – Amherst wouldn't have been the same without you. Thank you for patiently listening to me even when you had your own theses to worry about. There's no one else I would've wanted to spend so many late nights in the Science Center with.

Mom, Dad, and Matthew – thank you for always supporting me and for making my Amherst education possible. (And happy birthday, Dad!)

And lastly, to Amherst College – thank you for being my home for the past four years. I love this place more than I ever expected.

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1. Introduction

Just as credit cards transformed consumer spending in the 1980s, modern digital payment platforms like Venmo are revolutionizing commerce. Seminal behavioral economics research finds that credit cards elicit a higher willingness to pay (WTP) than cash, a phenomenon called the credit card premium (Hirschman 1979; Feinberg 1986; Prelec and Simester 2001). Unlike credit cards, though, the impact of digital payment platforms on consumer spending has been unknown until now. This paper is the first to study the impact of Venmo – or any specific digital payment platform – on consumer willingness to pay.

Understanding the impact of Venmo on willingness to pay is necessary given the increasing prevalence of Venmo and digital payments in general. Since their emergence in the early 2010s, digital payment platforms have skyrocketed in popularity and are now the preferred mode of transferring money to peers, especially for young people (Zhang, Tang, Zhao, Wang, Zheng, and Zhao 2017). Venmo is convenient; it can be used to pay for anything from a coffee to rent, payments are processed immediately, and funds can be transferred directly to a bank account. The convenience and popularity of Venmo have only been exacerbated by the current COVID-19 pandemic as consumers and businesses are now more likely to prefer contactless payments over methods that could transmit the virus, like cash or physical cards.

Despite its popularity, the effect of Venmo on consumer spending behavior has not been studied. Anecdotally, many college students say that money spent on Venmo feels “fake.” Is Venmo causing its users to spend more money? This paper investigates the existence of the *Venmo Effect*, our novel theory that Venmo increases the WTP of its users. Additionally, we propose three mechanisms that may contribute to the *Venmo Effect*: 1)

mental accounting, 2) priming, and 3) signaling. First, given Venmo's digital nature, users may not view their Venmo balance as fully fungible, making spending on Venmo less painful or guilt-inducing. Second, the social media feeds integrated in the Venmo app may prime spending generally or for specific purchases, making users more likely to spend. Third, Venmo may be used as a signal for wealth or social status, leading to higher WTP on Venmo for transactions that would send a positive signal to a user's peers. We investigate which, if any, of these three mechanisms drive the *Venmo Effect*.

To test the existence of a *Venmo Effect* and its potential mechanisms, we run an online experiment with college students that assesses the difference in average willingness to pay for purchases made using Venmo, debit cards, and credit cards. Participants are randomly assigned to one of five payment treatments: debit, credit, Venmo on the *Public* privacy setting, Venmo on the *Friends Only* privacy setting, and Venmo on the *Private* privacy setting. Half of the participants in the Venmo groups are also randomly assigned to a priming treatment that entails spending two minutes browsing the social feeds on the Venmo app, resulting in eight distinct treatment groups. All participants undergo ten incentive-compatible Becker, DeGroot, and Marschak (1964) lotteries for ten different low-cost consumer goods, which allows us to accurately measure participants' willingness to pay for each of the ten items.

A difference in means analysis of our experimental data provides two important insights about the role of Venmo: 1) a *Venmo Effect* exists, and 2) this *Venmo Effect* is driven by social influences rather than mental accounting. First, we find that the *Venmo Effect* does exist – the mean WTP for participants assigned to the Venmo treatment arms is 5% higher than for those assigned to debit and 17% higher than for those assigned to credit. In our fixed

effects regression estimation, the point estimates are consistent with a higher willingness to pay for Venmo users, though this finding lacks statistical significance.

In evaluating our three proposed mechanisms, we find that signaling and priming both influence consumer willingness to pay but mental accounting does not. For the signaling mechanism, we find that participants assigned to the *Friends Only* setting have a 21% lower mean WTP than the *Private* group and a 32% lower mean than the *Public* group. While this impact on WTP is in the opposite direction of our expected signaling effect, it still proves that Venmo users modify their spending based on who will see their transactions. In evaluating the priming mechanism, we find that participants assigned to the priming treatment have a 15% higher mean WTP than those assigned to no priming. The direction of the priming effect is not uniform across treatment groups; rather, it depends on the Venmo privacy setting. Priming increases WTP for the *Private* and *Public* groups (by 19% and 38%, respectively) but decreases WTP by 21% for the *Friends* group, heightening the existing signaling effect of each privacy setting on WTP. We do not find evidence of our proposed mental accounting mechanism, which suggests that the Venmo Effect is driven purely by social factors. More specifically, to evaluate the mental accounting mechanism, we focus on participants assigned to Venmo on the *Private* setting without priming, as those participants should be isolated from Venmo's social features; we find that the mean WTP for this *Venmo Private No Priming* group is about the same as the debit group (\$1.06 versus \$1.07) and slightly higher than the credit group (\$1.06 versus \$0.96).

In addition to our novel findings about the effect of Venmo on consumer WTP, a key contribution of our research is observing a higher WTP with debit than credit. This challenges older literature on the credit card premium, which finds that WTP for credit cards

is higher than cash. Given that debit functions similarly to cash (money is immediately withdrawn from a bank account, purchases do not accrue rewards, etc.), we would expect willingness to pay with debit to fall somewhere between cash and credit. However, we find the opposite; participants assigned to the debit treatment had a 11% higher mean WTP than those in the credit treatment. This may suggest that spending preferences differ across generations or have changed over time.

We segment the lottery items into four categories (*Food/Drinks*, *Office Supplies*, *Toiletries*, and *COVID-Related Items*) to determine whether different types of goods have different *Venmo Effects*. Across all item categories, the credit and *Venmo Private No Priming* treatments decrease WTP, and the *Venmo Private Priming* treatment increases WTP. Four of the eight treatments do not have consistent effects across all item categories. The *Venmo Friends No Priming* and *Venmo Friends Priming* treatments decrease WTP across all items, but the *Venmo Friends No Priming* treatment increases WTP for *Office* items and the *Venmo Friends Priming* increases WTP for *Toiletry* items. The *Venmo Public No Priming* and *Venmo Public Priming* treatments increase WTP across all items, but both decrease WTP for *COVID-Related* items and the *Venmo Public No Priming* treatment decreases WTP for *Office* items. However, these item category findings are not statistically significant.

The remainder of the paper proceeds as follows. Section 2 provides an overview of Venmo, its use, and how it compares to other similar digital payment platforms. Section 3 outlines existing literature on the effect of payment type on willingness to pay, particularly focusing on mental accounting and social influences on spending. Section 4 explains the behavioral economic theory which underlies the *Venmo Effect* and our predictions. Section 5 describes the features of our experiment designed to test the effect of Venmo on willingness

to pay; we describe the participants, specific experimental conditions, pilot, and our empirical strategy for the data collected. Section 6 details the results of our experiment and empirical analysis; we share our main results across the treatment groups and how those results vary for different types of goods. Section 7 concludes.

2. Description of Venmo

Venmo is a digital payment platform that allows users to send and receive payments to and from other Venmo users and select retailers. A Venmo transaction requires the initiator to indicate the user they want to send to or request from, enter the dollar amount of the transaction, and write a caption for the payment. A sent payment is immediately transferred; a requested payment must be first approved by the user who receives the request in order for the money to be transferred. All money received is added to a user's Venmo balance, which can then be transferred to a bank account. To send money, one can use their Venmo balance or link a bank account, debit card, or credit card. Venmo is generally free to use; fees are only incurred when using a credit card (3% of the transaction amount) or when initiating an instant bank transfer (1% fee capped at \$10, no fee for a 1-3 business day transfer). Venmo is only available for use in the United States. While it's becoming more common for retailers to accept Venmo, most Venmo transactions are peer-to-peer transfers. Zhang et al. (2017) find that the majority of Venmo transactions fall into the categories of food/drinks or transportation, with less popular categories being utilities and entertainment.

Venmo differs from other digital payment platforms like PayPal and Zelle as it includes a social media feed or a "social awareness stream" (SAS). In the Venmo app, users see three different social feeds: a *Public* feed, a *Friends* feed, and a *Private* feed. The default setting is *Public*, but users can change their privacy setting for all future transactions or for

one individual transaction. According to the Venmo website, *Public* transactions “will be shared on the Venmo public feed and anyone on the internet will be able to see it” and *Friends Only* transactions “will only be shared with your Venmo friends and with the other participant’s Venmo friends” (Venmo 2016). For *Private* transactions, however, Venmo “will not share the transaction anywhere other than your own personal feed and, if it’s a payment to another user, the feed of the other person in the payment” (Venmo 2016). As of 2016, these *Private* transactions made up approximately 51% of all Venmo transactions since Venmo became public to users in 2012 (Zhang et al. 2017). Venmo users are active and enthusiastic participants in the Venmo social media feeds. Venmo users are generally inclined to add friends on the app; half of Venmo users have at least 40 friends and 30% have over 100 friends (Zhang et al. 2017). While Venmo users describe themselves as indifferent or neutral towards the social feed in surveys, they report putting a lot of thought into the captions of their transactions on Venmo (Caraway, Epstein, and Munson 2017).

Venmo is incredibly popular, particularly with young people. In 2019, Venmo had over 40 million active accounts (Statista 2020). Over time, Venmo has been growing in total payment volume; from July 2019 to July 2020, volume increased by 54% from \$24 billion to \$37 billion (Statista 2020). Further, Venmo is also growing in user engagement, as average transaction frequency tripled from 2012 to 2016 (Zhang et al. 2017). Young people are much more likely to use digital payments and Venmo specifically. A 2017 survey finds that 65% of millennial respondents had used a mobile payment and 44% had used Venmo (Acker and Murthy 2018); similarly, Pew Research (2018) found that people in Generation X or younger made up 74% of survey respondents who use mobile payments.

3. Literature Review

3.1 Mental Accounting Overview

Under the assumption of the fungibility of money, a rational consumer would not change their behavior when using different forms of payment. However, there are systematic ways in which people act as if money is not fungible. Under mental accounting, people mentally segment their wealth into different accounts with different purposes (Thaler 1985; Shefrin and Thaler 1988; Thaler 1999). Mental accounting theory is applicable to our area of interest, form of payment; different payment methods may be assigned to different mental accounts, leading to a higher willingness to pay (WTP) for some payment types. Thaler (1999) identifies three critical components of mental accounting: 1) how outcomes are perceived and experienced, 2) the assignment of activities to specific accounts, and 3) the frequency with which accounts are evaluated. The second component – the assignment of activities to specific accounts – is most relevant to our research and warrants a deeper dive into the different ways that one can assign activities to various mental accounts: budgeting, the location of funds, or source of income (Thaler 1999).

First, one can budget. While budgeting is necessary, it can lead to irrational purchasing decisions if a person does not make a purchase because they've exhausted the purchase category's allocated budget, even if a different category still has remaining funds. For example, Heath and Soll (1996) find that participants who were told they received a \$50 parking ticket were more likely to spend money on admission to a play than participants who were told they spent \$50 on a basketball game; this is because the basketball game and play ticket fall into the same budget category in the participants' minds. A second manifestation of assigning certain activities to different mental accounts is based on the location of funds.

This is most commonly seen in savings; people put parts of their wealth in accounts that are off-limits, like a home or a retirement account with tax penalties.

Third, and most applicable to Venmo, consumers can assign spending to different mental accounts based on the way income is received. Unexpected income gains are more likely to be spent on hedonic purchases than expected income gains (Arkes, Joyner, Pezzo, Nash, Seigel-Jacobs, and Stone 1994). Further, consumers tend to spend at a similar level of frivolity as the source of the income; for example, O'Curry (1997) finds that people are likely to spend an income tax refund seriously but winnings from an office football pool frivolously. Building on this, Levav and McGraw (2009) find that the emotional label attached to a gain in income dictates how the money will be spent; more specifically, if consumers receive money in way that is associated with negative emotions, they will attempt to cope by spending it on "virtuous" or utilitarian products.

In a slightly more complex understanding of mental accounting, Prelec and Loewenstein (1998) introduce pain of payment in their double entry mental accounting model; for every purchase made, consumers experience some level of pain from spending money and some amount of positive utility from the purchase. If the pain of payment is separated temporally or mentally from the consumption of the purchase (called weak coupling), the product can be consumed as if it were free, leading to consumers being more willing to spend (Prelec and Loewenstein 1998). Thus, payment forms with weaker coupling – like credit cards – have a lower pain of payment and therefore elicit higher WTP. In addition to pain of payment, Morris (2018) introduces the idea that trackability may play a role in feelings of pain associated with spending; consumers may prefer to use less trackable

payment methods like cash for purchases they associate with financial irresponsibility in order to lessen the guilt they feel.

3.2 Willingness to Pay with Credit Cards versus Cash

Existing literature, both in the lab and the field, shows that consumers have a higher willingness to pay when using credit cards than when using cash, called a “credit card premium.” Hirschman (1979) finds significantly higher spending with credit cards than cash. Even just the presence of credit card stimuli, like logos, leads to higher willingness to pay (Feinberg 1986). In response to criticism that Feinberg (1986) primarily tests hypothetical transactions, Prelec and Simester (2001) incorporate real-money transactions into their analysis of credit cards, finding that credit cards do causally increase consumer willingness to pay, sometimes up to 100%. In addition to the literature on point-of-purchase, research also shows that people tend to remember cash transactions better than credit card transactions (Srivastava and Raghurir 2002). This ability to recall past spending can impact willingness to pay; Soman (2001) finds that that people are better at remembering past spending with checks than past spending with credit cards, leading to lower salience and vividness with credit cards and thus a higher willingness to pay. In addition to eliciting a higher WTP, credit cards also impact consumer perceptions and evaluations of products; Chatterjee and Rose (2012) find that consumers primed with credit cards focus on the benefits of a potential purchase while those primed with cash focus on the costs. These proposed mechanisms behind the credit card premium vary from classical conditioning (Feinberg 1986) to transparency of payment (Raghurir and Srivastava 2008) and memory processes (Soman 2001), but all fall under the umbrella of psychological factors and do not account for external social factors on spending.

3.3 The Rise of Digital Payment Platforms and Venmo

The willingness to pay literature has slightly started to expand to digital payment platforms. Huang, Ghosh, Li, and Ince (2020) examine the effect of digital payment platforms on the endowment effect. They find that digital payment platforms lead to a higher WTP for buyers but do not impact willingness to accept (WTA) for sellers, effectively decreasing the endowment effect. However, there is still much to be done; Huang et al. (2020) study digital payments in the aggregate rather than one specific platform. Additionally, cash may not be a sufficient control group for modern spending decisions, and they do not include credit cards as an additional comparison.

Digital payment platforms are even more relevant given the COVID-19 pandemic. As banknotes and coins were suspected to carry the virus, both consumers and businesses began to prefer non-cash payments. Credit and debit cards were not an ideal alternative as they have shared surfaces like pin pads and pens. Thus, contactless digital payments seemed to be the safest option. Zelle saw increases in use and enrollment since March 2020 and PayPal saw 7.4 million new accounts in April 2020 alone, a 135% increase (Toh and Tran 2020). As digital payment platforms become increasingly popular, it is even more important to have a strong understanding of how they impact consumer behavior.

3.4 Social Influences on Spending

Existing social psychology research shows that, at a very basic level, “we often do what we see others doing” (Dijksterhuis and Bargh 2001). More specifically, behavior is influenced by what is made salient. For example, increasing a brand’s accessibility in memory increases the probability of consumers choosing that brand (Nedungadi 1990). Even when people are not aware of being primed, priming impacts their behavior (Bargh, Chen,

and Burrows 1996). These findings are not limited to traditional in-person transactions; existing literature shows that social media use lowers consumers' self-control, leading to more impulsive behavior like choosing unhealthy foods (Wilcox and Stephen 2013) and also causes an overuse of credit for Americans (Thoumrungroje 2018). In the context of willingness to pay, this lowered self-control may mean that that consumers have a higher WTP due to the social aspect of Venmo.

Priming is a reactive social influence; consumers change their spending behavior in response to external stimuli. But another category of social influence is anticipatory: consumers may change their spending behavior because they expect something to happen in the future. At our cores, humans have a fundamental need to belong (Baumeister and Leary 1995). This need for belonging often translates to consumer spending in the form of conspicuous consumption. The prevalence of conspicuous consumption, defined as the spending of money in an attempt to impress others, is supported by survey data (Podoshen and Andrzejewski 2012). Indeed, social psychology research shows that consumers will purchase certain products or even lie about products in order to impress others (Leigh and Gabel, 1992; Sengupta, Dahl, and Gorn 2002); further, even a noninteractive social presence influences consumer behavior (Argo, Dahl, and Manchanda 2005). People also tend to incorporate more variety into their spending decisions when they know their behavior is public (Ratner and Kahn 2002).

Given the presence of social media feeds in the Venmo app (as described in *Section 2*), any study of Venmo's influence on consumer willingness to pay must examine the influence of social factors in addition to a more traditional lens like mental accounting.

3.5 Limitations of Existing Research

The existing literature about the influence of payment form on willingness to pay is limited. First, it focuses on mental accounting as the primary mechanism and does not incorporate social impacts on spending. Second, it studies only traditional payment methods (like cash and credit) or aggregated digital payments rather than individual digital payment platforms. Our experiment contributes a novel perspective to these ongoing conversations by focusing solely on Venmo, including multiple comparison payment forms, focusing on college students, and introducing social factors in addition to mental accounting.

4. Theory

In our experiment, we expect the *Venmo Effect* to be demonstrated by higher willingness to pay estimates for participants using Venmo than those using credit and debit cards. We also propose three different mechanisms that may contribute to this *Venmo Effect*: 1) mental accounting, 2) priming, and 3) signaling.

4.1 Mental Accounting

Mental accounting implies that consumers using Venmo will spend more readily because funds received via Venmo are considered “frivolous.” As of 2016, over half of identifiable Venmo transactions were for food or drinks (Zhang et al. 2017). Additionally, social networks on Venmo are very closely clustered, meaning money received on Venmo tends to come from friends and family (Zhang et al. 2017). In contrast, money held as cash or in a checking account (which is then accessible via credit or debit cards) is often earned through work, a less trivial source of income. Since people are more likely to spend money from a windfall at the same level of frivolity as the windfall itself (Thaler 1999; Muehlbacher and Kirchler 2019), Venmo users are more willing to spend their Venmo balance on non-

essential purchases, like entertainment, than if they had to use cash, debit, or a credit card. This means that Venmo leads to a higher willingness to pay – both for those specific “frivolous” items and overall – than cash or cards.

But would someone who only sends money and never receives a Venmo payment still demonstrate the *Venmo Effect*? First, this situation is unlikely; Zhang et al. (2017) find that users are likely to both send and receive money and that interaction reciprocity on Venmo is similar to Facebook and greater than Twitter. Regardless of the level of payment reciprocity on Venmo, though, a person who has only sent payments on Venmo will demonstrate a higher WTP than with cash or credit cards. This is due to another application of mental accounting: budgeting. Standard economic theory assumes that consumption levels depend on a person’s wealth and thus a change in wealth will produce the same change in income (Friedman 1957). Shefrin and Thaler (1988) propose a modified version of this life-cycle model and claim that gains in wealth that are transferred to less tempting mental accounts (like home equity or a designated retirement account) are less likely to be spent. But in order to decide how to spend your money, you must have a sense of what your liquid assets are. Most people think of their disposable income as either the balance in their bank account, the contents of their wallet, or some combination of the two. Since the money in a person’s Venmo balance is not reflected in their bank statements or their physical wallet, it means that any money in Venmo is likely not being considered as a part of their wealth and thus not being included in any formal or informal budget. This is similar to gift cards, which are found to lead to more hedonic spending (Helion and Gilovich 2014; White 2006). As money in Venmo has not been allocated to any specific purpose or budget, it can be spent freely, meaning that consumers have a higher willingness to pay.

Even if Venmo is included in a person's budget, it is still less painful to spend with Venmo than with other sources. Incorporating Prelec and Loewenstein (1998)'s double-entry mental accounting model, we assume that for every transaction, a consumer gets some negative amount of utility (or "pain") from spending money, which varies depending on form of payment. Raghurir and Srivastava (2008) find that forms of payment with lower transparency (i.e., less vividness) lead to less pain of payment for consumers. Given Venmo's online format, it has lower transparency in spending because numbers in an app do not have a physical association with spending in the way that handing over cash or a credit card does. Thus, consumers are more likely to spend with Venmo than with debit or credit cards because pain of payment is lower. This is particularly relevant for a "guilty" purchase. For example, if a person is buying an item that they can't afford or is bad for their health, they may choose to use Venmo because it would feel less "real," reducing overall feelings of guilt.

One potential criticism of this theory is that Venmo users are simply responding to transaction costs. If Venmo users could not transfer money out of their accounts, then it would be rational for them to treat their Venmo balance differently because it would not be a perfect substitute for cash or credit. However, money in a user's Venmo balance is easy to transfer directly to their bank account; users can choose between an instant transfer for a 1% fee (capped at \$10) or a free transfer that takes 1-2 business days. Transferring money to a bank account would remove any windfall, budgeting, or pain of payment effects, making purchases more painful and guilt-inducing; this is exactly why Venmo users choose not to transfer their money out of Venmo. Shapiro and Burchell (2012) find that financial anxiety triggers financial avoidance, meaning that people who feel guilty or anxious about spending

may choose to avoid reminders of their poor behavior. College students who overspend tend to have higher levels of anxiety about money (Roberts and Jones 2005). Thus, Venmo users prefer to keep money in their Venmo balance – even if they realize that it leads to irrational overspending – because they do not want to feel the guilt associated with that spending. Actively choosing to keep money in the Venmo balance provides a psychological benefit from Venmo that cash and credit do not provide.

Overall, consumers view money in their Venmo balance differently than other payment forms, causing a higher willingness to pay with Venmo than with debit or credit cards. While it is difficult to isolate the mental accounting mechanism, we can approximate it by having participants 1) not look at the app prior to purchase decisions and 2) set their Venmo privacy settings to *Private* so no one will see their transactions. In this comparison of participants using Venmo on the *Private* setting without priming and participants using debit or credit cards, we expect that WTP will be higher with Venmo than with credit or debit cards even in the absence of Venmo’s social factors.

4.2 Priming

In addition to mental accounting, we identify two separate social influences on consumers’ willingness to pay when using Venmo. First, the Venmo social media feeds may prime users to spend more money. More specifically, if Venmo users see other users’ transactions in Venmo app, it may make them more willing to spend. This priming could be limited to the specific items seen on the Venmo feed; for example, seeing a friend use the pizza emoji as their Venmo caption may make a user want to order pizza. However, it also could be a more general priming effect that makes users more likely to spend money. Simply

seeing other people engaging in transactions could make a Venmo user want to spend regardless of the type of purchase.

By incorporating a priming treatment, our experiment tests whether seeing other users' transactions in the Venmo feed makes spending money more salient, thus making users more likely to spend money themselves. We expect participants who have been primed by scrolling through the Venmo feed for two minutes to have higher willingness to pay estimates than those who were not primed. Additionally, we expect priming to have a larger effect on the *Friends* feed than the *Public* or *Private* feeds as we believe college students are more easily influenced by their peers than strangers.

4.3 Signaling

College students have a desire to fit in and impress others around them (Gardner and Steinberg 2005). This affects financial decision making as college students are more likely to overspend on their credit cards when they are in the context of shared social experiences with their peers; Sotiropoulos and D'Astous (2012) find that this overspending is not an exogenous effect of credit card usage but an interaction between social norms and credit card possession. As Venmo has built-in social media feeds, spending on Venmo must be studied in the context of the social interactions that influence spending.

Venmo's second social influence on WTP is through the signaling of status and/or wealth. In addition to the priming mechanism of seeing others' transactions, Venmo users may spend more in anticipation of other users seeing their own transactions. One way for college students to signal their social or financial status may be public Venmo transactions. In the Venmo feed, both parties involved in a transaction are shown, assuming the transaction is not private. Thus, paying a person who has a high social status may have value to someone

who wants to gain popularity. A different (and potentially concurrent) type of signaling on Venmo is wealth signaling. Although the dollar amount of a transaction is not public, users can write a caption that suggests a high dollar value; for example, they could include the name of an expensive restaurant or brand. Similarly, engaging in transactions frequently could suggest a comfortable financial status.

If a Venmo user's non-private transaction can impress their peers, then using Venmo can provide additional value on top of the innate value of the good or service being purchased. Thus, we expect people who get this signaling benefit to have higher willingness to pay estimates than users who would not receive any status boost. In our experiment, we test this theory by comparing users across privacy settings; we expect both the *Public* and *Friends* settings to elicit higher WTP estimates than the *Private* setting because users will recognize that others may see their transaction. Additionally, we expect the *Friends* setting to elicit a higher WTP than the *Public* setting because people tend to care more about the opinions of those close to them than strangers.

5. Experimental Design

To test the *Venmo Effect*, we use an online experiment with 261 undergraduates who currently attend a college or university in New England. The median time spent completing the experiment was 22 minutes. Each participant was compensated with a \$5 Amazon e-gift card via email upon completion. The survey was created with Qualtrics and accessed through a link sent to participants. *Section 8.2* contains screenshots of questions from the online experiment.

5.1 Participants

Participation was limited to undergraduate students who currently attend a college or university in New England. The specific institutions represented are Bates College, Boston College, Bowdoin College, Colby College, Hamilton College, Middlebury College, Mount Holyoke College, Northeastern University, Smith College, Trinity College, Tufts University, University of Massachusetts-Amherst, University of Vermont, Wesleyan University, and Williams College. Participants were sourced through faculty at their institution's economics and/or psychology departments. Prior to the experiment, all participants answered a series of screening questions, which allows us to screen out non-college students and non-Venmo users. To qualify as a Venmo user, each participant needed to have a Venmo account, have the Venmo app downloaded, and either have a nonzero Venmo balance or an alternate payment form linked to their Venmo account. The other disqualifying factors were being under 18 years old and not possessing either a debit card or a credit card.

Researchers often use college students for lab experiments, both in economics and psychology research. This choice is often out of convenience; college students are located near the lab and generally willing to participate in exchange for low compensation. While using college students can sometimes be limiting for experimenters, in this case college students are the demographic of interest for testing the *Venmo Effect*. Most of the existing literature on willingness to pay with cash and credit cards is at least 20 years old, meaning that participants were from a different generation than today's college students. Over time, young people's relationship with and views of various payment forms may have changed, especially for digital payment platforms like Venmo. A 2017 survey finds that 65% of millennial respondents had used a mobile payment and 44% had used Venmo (Acker and

Murthy 2018); similarly, Pew Research (2018) finds that people in Generation X or younger made up 74% of respondents who use mobile payments. Additionally, the social effects of Venmo may be particularly relevant for college students as young people are more susceptible to influences of conspicuous consumption and peer pressure. For example, Gardner and Steinberg (2005) find that college-aged participants are 50% more likely to engage in risky behavior after being exposed to peers while they find no peer impact on adults. In the context of consumption decisions, research shows that college students see spending money as necessary to build friendships and feel like they belong (McClure and Ryder 2017). Overall, we use college students as we expect them to be most susceptible to the *Venmo Effect* due to their technological literacy and social impressionability.

5.2 Treatments

Participants are assigned to one of five payment form treatment groups: 1) debit card, 2) credit card, 3) Venmo on the *Private* setting, 4) Venmo on the *Friends Only* setting, and 5) Venmo on the *Public* setting. Participants are told that they can only use their assigned form of payment for the rest of the experiment. The Venmo groups are asked to open the app and change their privacy settings to their assigned setting (*Public*, *Friends Only*, or *Private*). Privacy settings can easily be changed back after the experiment. Debit and credit are our comparison groups; debit is a proxy for cash, which would not have been feasible to exchange in an online experiment. Additionally, for participants in any of the three Venmo payment groups, there is a second treatment: priming. Regardless of assigned privacy setting, all the Venmo assignees are randomly assigned to either priming or no priming. Participants assigned to priming are asked to browse through the *Public* Venmo feed for 2 minutes;

participants assigned to no priming are not informed of this assignment and simply proceed with the experiment.

Limiting our analysis to only Venmo, credit, and debit would only allow us to identify whether a *Venmo Effect* exists; we would not be able to examine the mechanisms behind it. Thus, we include the additional privacy setting and priming variations to determine whether social factors on Venmo contribute to a *Venmo Effect*. We believe this insight is worth the reduction in power caused by the additional treatments, though we recognize that a larger sample size would be ideal.

5.3 Experiment

The experiment consists of ten incentive-compatible Becker, DeGroot, and Marschak (1964) lotteries for ten different low-cost household goods. As is standard in a Becker, DeGroot, and Marschak (henceforth BDM) lottery, participants first indicate their willingness to pay for a given item. Then, a price is randomly selected from a reasonable range; this range is not shared with participants in order to avoid anchoring effects (Wertenbroch and Skiera 2002). If the random price is less than or equal to the price the participant indicated as their maximum price, then they must purchase the good at the randomly drawn price. If the randomly drawn price is greater than the participant's indicated maximum price, then they are not given an opportunity to buy the good.

In our experiment, we conduct ten BDM lotteries for ten different common low-cost items: a notebook, a pen, an adhesive phone wallet, a can of soda, a pack of gum, a granola bar, a bottle of coffee, a bar of soap, a tube of toothpaste, and a cloth face mask. In order to avoid any "winner" or "loser" effects, we have participants list their maximum price for all ten items before drawing any prices; essentially, we run ten BDM lotteries simultaneously

(rather than back-to-back, as the previous lottery outcomes could influence the subsequent WTP estimates). Thus, only after the participants provide their WTP for all ten items is a random price between \$1.00 and \$5.00 drawn for each good. Participants are then shown all the random prices followed by whether they won ($\text{price} \leq \text{WTP}$) or lost ($\text{price} > \text{WTP}$) each lottery. Appendix Figures 11 and 12 demonstrate how lottery results are communicated.

There are three potential outcomes for each participant: 1) win zero lotteries, 2) win one lottery, or 3) win multiple lotteries. Those who do not win any lotteries are not given the opportunity to transact and thus proceed to final demographic questions. Those who win one lottery are asked to purchase the item they won at the randomly drawn price via their assigned payment form. For budget purposes and simplicity, those who win multiple lotteries are only asked to purchase one of their winning items, which is chosen randomly. After the random selection, they pay for their item at the randomly drawn price via their assigned payment form, just like those who win only one lottery.

All transactions are completely secure for participants. Those assigned to Venmo are asked to pay a Venmo account created for the experiment (@WillingnessToPayResearch). Those assigned to pay with debit or credit are asked to pay through Square, a secure 3rd party credit card processing service, which opens in a new tab from the online experiment. If participants do not feel comfortable, they are allowed to abstain from paying; only 1.6% of participants who won at least one lottery chose not to pay. If a participant does not pay, they are asked why; the provided options are 1) feel uncomfortable providing payment information online, 2) do not think the item was worth the randomly drawn price, 3) never planned to submit a payment, or 4) do not possess the assigned payment form. The only response that does not compromise the participant's WTP estimates is the first option, that

they did not feel comfortable entering their payment information online. The other answers suggest that the participant either misreported personal information or inaccurately estimated their WTP, both of which question the integrity of the data they provided. Thus, if a participant selects anything other than feeling uncomfortable submitting a payment online, the associated observation is dropped from the dataset.

After paying (or, in the case that the participant had zero wins, directly after the lotteries), participants answer a series of follow-up questions. We ask participants about their normal spending habits, payment preferences, Venmo usage (how often they use Venmo, how many friends they have on Venmo, how much money is in their Venmo balance, etc.), and social media usage. Next, we ask demographic questions and what participants thought the purpose of the experiment was. Lastly, participants are debriefed, the complete text of which is shown in Appendix Figure 13. After completing the experiment, each participant receives a \$5 Amazon e-gift card via email. If they purchased an item during the experiment, it is mailed to them the following business day.

5.4 Pilot

Prior to running the full experiment, we executed a pilot to assess levels of attrition and payment compliance. We had originally planned to use Amazon Mechanical Turk to source participants, so the pilot consisted of 49 participants on mTurk. Out of the 49 total participants, 25 made it through the screening questions and won at least one lottery. All of those 25 claimed that they paid for their winning item, but only one participant actually submitted a payment. More importantly, we found that 21 of these 25 responses were completed by one person who created 21 different mTurk accounts to avoid the site's attempt

limits. Given that this data was essentially unusable, we modified our experimental design prior to running the full experiment.

First, we needed a new source of participants who are less dishonest and more naïve than those on mTurk. Thus, to collect the rest of our data, we decided to reach out directly to college students in New England in hopes that a more personal connection would foster sincerity in respondents. Prior to the pilot, while we were still designing the experiment, we conducted focus groups with Amherst College students to test whether the survey instructions were clear. During these sessions, most students said they would have submitted a payment if they were participating in the real experiment. Therefore, it seems that students who have a more personal connection to the researchers (e.g., are a part of the same institution or academic network) are more trusting and less dishonest. Since many students at Amherst College were already familiar with the experiment, we decided to use students at other colleges and universities in New England.

Second, we added more attention checks and verification questions at the beginning of the experiment to screen out participants who will not pay. Immediately following the informed consent page, we added a question that asks participants if they would be willing to make a payment during the experiment. During each lottery, we added a verification question that would appear if a participant listed a willingness to pay over \$20. We also added follow-up questions during the payment stage, so a participant can indicate why they did not pay; this way, we can tell whether the data is still usable even if the participant did not pay, like if they were simply concerned about the security of an online transaction. Adding these verification questions and attention checks increased compliance and led to more accurate WTP estimates than in the pilot.

5.5 Empirical Strategy

The empirical strategy outlined below aims to answer three questions: 1) Does our experimental data show evidence of the *Venmo Effect*? 2) Which, if any, of our three proposed mechanisms are supported by the experimental data? 3) Does the *Venmo Effect* vary depending on the type of item being purchased?

To answer the first two questions, we compare mean WTP across the eight treatment groups. For the general *Venmo Effect*, we compare mean willingness to pay for participants assigned to Venmo and those assigned to the debit or credit treatments; we expect participants to have a higher mean WTP with Venmo than with debit or credit cards. To assess the mental accounting mechanism, we measure the impact of Venmo in the absence of its social features by comparing mean WTP of participants assigned to the *Venmo Private No Priming* treatment to the mean WTP of those assigned to debit. The *Venmo Private No Priming* treatment group is the closest we can get to isolating the mental accounting mechanism of Venmo; participants in that group should not experience any social influences because they know that no one will see their transaction and are not instructed to view any other transactions prior to estimating their WTP. For the signaling mechanism, we compare mean WTP across the three privacy setting treatments: *Private*, *Friends Only*, and *Public*. This allows us to test whether users who know their friends will see their transactions have a higher WTP than those who know that strangers or no one will see their Venmo payments; we expect participants who use the *Friends* setting on Venmo to have higher WTP estimates than those who use the *Public* or *Private* settings. And, finally, to test the priming mechanism, we compare mean WTP for participants who were assigned to priming to mean WTP for those who were not assigned to priming; we expect participants who scroll through

the Venmo social feed to have higher WTP estimates than those who do not. As the impact of priming may depend on the privacy setting, we also examine how mean WTP varies within each of the privacy settings; for example, the difference between mean WTP for *Venmo Public No Priming* and *Venmo Public Priming* represents the impact of priming when using the *Public* setting. We expect the largest impact of priming to be for the *Friends Only* group.

In order to account for variation in WTP caused by differences across the ten items and the potential influence of differing levels of experience with Venmo, we also conduct the following ordinary least squares regression:

$$WTP_{i,j} = \beta_0 + \beta_1 Credit_i + \beta_2 VenmoPrivateNoPriming_i + \beta_3 VenmoPrivatePriming_i + \beta_4 VenmoFriendsNoPriming_i + \beta_5 VenmoFriendsPriming_i + \beta_6 VenmoPublicNoPriming_i + \beta_7 VenmoPublicPriming_i + \beta_8 Item_j + \beta_9 Controls_i + \varepsilon_{i,j}$$

where i represents an individual respondent and j represents the lottery item. $WTP_{i,j}$, the outcome variable, is the maximum price listed by the participant. The variables $Credit_i$, $VenmoPrivateNoPriming_i$, $VenmoPrivatePriming_i$, $VenmoFriendsNoPriming_i$, $VenmoFriendsPriming_i$, $VenmoPublicNoPriming_i$, and $VenmoPublicPriming_i$ are binary indicators for whether the individual was assigned to that given treatment arm; the debit treatment is omitted. $Item_j$ represents item-level fixed effects and $Controls_i$ are control variables that measure Venmo usage, specifically age of Venmo account, Venmo balance, number of friends on Venmo, percentage of spend via Venmo, number of linked payments on Venmo, monthly transactions, monthly inflow, and monthly outflow.

This regression estimation allows us to answer our empirical questions through postestimation testing. For the general *Venmo Effect*, the difference between the Venmo WTP estimates and the debit WTP estimates are measured by β_2 , β_3 , β_4 , β_5 , β_6 , and β_7 . The

existence of the *Venmo Effect* would be supported if these coefficients are positive and statistically significant. For the mental accounting mechanism, the coefficient of interest is β_2 . For the signaling mechanism, we compare jointly β_2, β_3 with β_4, β_5 and with β_6, β_7 . For the priming mechanism, we compare jointly $\beta_2, \beta_4, \beta_6$ with $\beta_3, \beta_5, \beta_7$. For the within-privacy setting analysis, we compare the respective priming and no priming coefficients; for example, we compare β_2 to β_3 to see the impact of priming on WTP for the *Private* setting.

To test whether different types of items may have different *Venmo Effects*, we split the ten items into four categories: 1. *Food/Drinks* (the can of Coca Cola, granola bar, pack of gum, and bottle of coffee), 2. *Office Supplies* (the notebook, pen, and phone wallet), 3. *Toiletries* (the toothpaste and soap), and 4. *COVID-Related* (the cloth face mask). We repeat the previous regression estimation omitting the fixed effects and controls but introducing indicator variables for each category and interaction terms between the treatment and category variables. We compare the coefficients for the interaction terms across payment types within a given category of items. We expect that items for which Venmo is typically used, like food and drinks, will have a larger *Venmo Effect* than items less commonly purchased on Venmo, like office supplies or toiletries.

6. Results and Discussion

6.1 Summary Statistics

Summary statistics for the participants in our experiment are presented in Table 1. A total of 533 participants attempted the experiment. We keep observations only from the 261 participants who completed the experiment; this excludes anyone who was screened out, failed attention check questions, or quit partway through. We drop observations from any participants who misreported paying for their winning item ($n = 6$) or who did not pay for

any reason other than security concerns ($n = 1$). We also drop observations from participants who put zero for all of their WTP estimates ($n = 11$) as they may have been understating their true willingness to pay to avoid being asked to purchase an item. To further eliminate potentially dishonest respondents, we drop observations of any participants whose answers to the initial screening questions were inconsistent with their answers to final demographic questions ($n = 6$); specifically, we drop observations of participants who initially said they have one or more debit cards but later said they do not have a debit card (or a similar inconsistency for credit card or Venmo usage). Additionally, we drop both observations from one participant who completed the survey twice ($n = 2$). We are left with 2,350 observations from 235 unique participants. The mean WTP across all treatment arms is \$1.13 (s.e. (\$0.051)) and the median is \$0.50. We drop one outlier WTP estimate of \$100, resulting in 2,349 observations with a mean WTP of \$1.09 (s.e. (\$0.029)) and median WTP of \$0.50.

Table 1 shows mean values of selected variables across the eight treatment groups. The selected variables include demographic information, measures of Venmo usage, measures of social media usage, and mean willingness to pay estimates. In general, there are not statistically significant differences in observables across the eight treatment groups but there are a few exceptions that do not seem to follow any trends across treatment groups or variables. For a complete set of pairwise t-tests, see Appendix Table 1.

The average participant from our sample is more female and wealthier than the average college student in the United States. The gender composition of the sample is 62.6% female, 35.3% male, 2.1% nonbinary. A majority of participants have a household income greater than \$100,000, while the remaining participants are roughly evenly distributed between \$0 and \$100,000. Participants represent 15 different colleges and universities in

New England, but three institutions account for a majority (61.3%) of participants; University of Massachusetts-Amherst comprises 32.8% of the total sample, Williams College comprises 14.9%, and Colby College comprises 13.6%. Participants represent all undergraduate years of study, with the average year of study being roughly between a sophomore and junior. The average participant is approximately 20 years old. Participants are majority white; 68.9% of participants indicated that they identify as white, compared to 29.8% identifying as Asian, 3.4% identifying as Black, and 0.4% identifying as American Indian or Alaska Native. Only 7.2% of all participants indicated that they are of Hispanic, Latino, or Spanish origin.

Table 1: Summary Statistics Across Treatment Groups

	Credit	Debit	Venmo Private No Priming	Venmo Private Priming	Venmo Friends No Priming	Venmo Friends Priming	Venmo Public No Priming	Venmo Public Priming
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Mean/SE	Mean/SE	Mean/SE	Mean/SE	Mean/SE	Mean/SE	Mean/SE	Mean/SE
N	33	50	27	22	30	23	24	26
<i>Demographic Variables</i>								
Age	20.424 [0.238]	20.180 [0.166]	20.222 [0.235]	19.909 [0.217]	19.900 [0.241]	20.087 [0.288]	20.458 [0.282]	20.038 [0.232]
Year Of Study	2.758 [0.180]	2.720 [0.149]	2.630 [0.221]	2.364 [0.224]	2.367 [0.222]	2.696 [0.255]	2.875 [0.243]	2.615 [0.193]
Female	0.545 [0.088]	0.700 [0.065]	0.667 [0.092]	0.500 [0.109]	0.800 [0.074]	0.609 [0.104]	0.542 [0.104]	0.538 [0.100]
White	0.818 [0.068]	0.640 [0.069]	0.778 [0.082]	0.500 [0.109]	0.633 [0.089]	0.739 [0.094]	0.708 [0.095]	0.692 [0.092]
Household Income	3.759 [0.332]	4.000 [0.229]	3.520 [0.417]	3.429 [0.313]	4.333 [0.305]	3.750 [0.383]	4.048 [0.348]	3.957 [0.330]
<i>Venmo Usage</i>								
Venmo Balance	147.302 [98.291]	83.029 [23.943]	40.069 [12.291]	139.936 [51.672]	48.050 [14.647]	153.994 [89.637]	81.218 [45.619]	105.323 [44.660]
Years with Venmo Account	2.970 [0.236]	3.080 [0.173]	3.370 [0.234]	2.571 [0.289]	2.724 [0.253]	2.909 [0.254]	3.000 [0.314]	2.808 [0.266]
Number of Friends on Venmo App	104.182 [17.282]	96.640 [10.882]	109.407 [15.281]	79.727 [14.672]	69.000 [10.986]	135.522 [24.341]	105.708 [17.329]	112.615 [17.174]
Venmo Transactions Per Month	4.970 [2.062]	2.718 [0.305]	2.926 [0.420]	1.977 [0.306]	3.267 [0.758]	4.261 [0.801]	2.792 [0.420]	3.269 [0.655]
Percentage of Money Spent via Venmo	12.970 [1.476]	14.651 [2.031]	15.222 [2.137]	17.955 [3.953]	17.600 [2.312]	21.913 [4.099]	15.229 [2.856]	17.327 [3.786]
<i>Social Media Usage</i>								
Number Of Social Media Sites Used	5.303 [0.321]	5.300 [0.262]	5.407 [0.407]	4.773 [0.431]	4.733 [0.321]	4.727 [0.510]	4.792 [0.390]	4.500 [0.404]
Average Number of Hours Spent on Social Media Per Day	2.864 [0.471]	2.925 [0.242]	2.778 [0.371]	3.114 [0.431]	2.667 [0.219]	2.774 [0.288]	3.219 [0.292]	3.000 [0.365]
<i>WTP Estimates</i>								
Average WTP for All Items	0.955 [0.147]	1.068 [0.123]	1.058 [0.185]	1.712 [0.491]	0.997 [0.136]	0.792 [0.131]	1.110 [0.193]	1.530 [0.252]
Average WTP for Food or Drink Items	0.820 [0.113]	0.819 [0.111]	0.910 [0.143]	0.968 [0.162]	0.752 [0.114]	0.573 [0.108]	0.846 [0.145]	1.230 [0.199]
Average WTP for Office Supply Items	0.845 [0.168]	1.001 [0.151]	1.059 [0.234]	1.213 [0.286]	0.995 [0.179]	0.657 [0.149]	1.008 [0.258]	1.565 [0.340]
Average WTP for Toiletry Items	0.273 [0.043]	0.327 [0.042]	0.346 [0.066]	0.376 [0.059]	0.295 [0.048]	0.302 [0.061]	0.367 [0.066]	0.483 [0.077]
Average WTP for COVID-Related Items	1.553 [0.472]	1.784 [0.235]	0.994 [0.227]	6.602 [4.465]	1.617 [0.397]	1.234 [0.283]	1.759 [0.324]	1.823 [0.381]

Note: This table reports the mean values for selected variables across the eight treatment and control groups in our experiment. Pairwise t-test values can be found in Appendix Table 1. Household income is categorical; 0 represents income under \$20,000, 1 represents \$20,000-\$34,999, 2 represents \$35,000-\$49,999, 3 represents \$50,000-\$74,999, 4 represents \$75,000-\$99,999, and 5 represents \$100,000+

The average participant in our experiment is an active Venmo user but uses credit or debit cards as their primary payment method. At the time of the experiment, participants had an average of 100 friends on the Venmo app and \$97 in their Venmo balance (median of \$11). Participants use Venmo for an average of 3.3 transactions per month and estimate that they spend \$23 and receive \$27 on Venmo in an average month. The average participant uses their credit card the most often, followed by debit, Venmo, cash, and any other digital payment platforms, in that order. Similarly, Venmo transactions account for 16% of participants' total spending, which is less than credit or debit but more than cash or other digital payment platforms. Participants use an average of 1.4 other digital payment platforms in addition to Venmo, the most popular of which is PayPal.

6.2 Main Results

Between the Venmo, debit, and credit treatment arms, participants assigned to the Venmo treatments have the highest mean WTP (\$1.12; s.e. (\$0.037)), followed by debit (\$1.07; s.e. (\$0.058)), and then credit (\$0.96; s.e. (\$0.074)). This difference in means is only statistically significant at the 12.5% level; all other differences in means reported in this section are significant at the 5% level. It is important to note that while these differences might seem low in magnitude, they represent large percentage changes in WTP; given that the mean WTP for the credit group is \$0.96 (s.e. (\$0.074)), an increase of \$0.16 represents a 17% increase in WTP.

Within Venmo, the highest mean WTP is for the *Public* setting (\$1.33; s.e. (\$0.072)), followed by the *Private* setting (\$1.15; s.e. (\$0.065)). The *Friends Only* setting has a much lower mean WTP (\$0.91; s.e. (\$0.052)), 32% less than *Public* and 21% less than *Private*. Also within Venmo, those assigned to priming have a 15% higher mean WTP (\$1.21; s.e.

(\$0.057)) than those assigned to no priming (\$1.05, s.e. (\$0.047)). The impact of priming on WTP depends on privacy setting; within those assigned to the Venmo *Private* treatment, WTP is 19% higher for those who underwent priming (\$1.26; s.e. (\$0.104)) than those who were not primed (\$1.06; s.e. (\$0.082)). Similarly, for the Venmo *Public* treatment, the mean WTP of participants who were primed is 38% greater (\$1.53; s.e. (\$0.108)) than the mean WTP of those who were not primed (\$1.11; s.e. (\$0.088)). In contrast, within those assigned to the *Friends* treatment, those who were primed have a 21% *lower* mean WTP (\$0.79; s.e. (\$0.068)) than those who did not undergo priming (\$1.00; s.e. (\$0.076)). Thus, priming is associated with a higher WTP for the *Private* and *Public* settings but a lower WTP for the *Friends Only* setting.

Across all eight treatment groups, we find that mean WTP is highest for participants assigned to *Venmo Public Priming* (\$1.53; s.e. (\$0.108)) and lowest for participants who were assigned to *Venmo Friends Priming* (\$0.79; s.e. (\$0.068)). The first row of the “WTP Estimates” section in Table 1 shows these differences in means across the eight treatment groups. The subsequent 4 rows show the differences in means across the groups for specific categories of goods; these results are discussed in greater detail in *Section 6.3*.

Despite removing the one outlier of \$100, the WTP estimates are still highly skewed (skewness of 2.32). Thus, we examine the differences in median WTP across treatment groups to determine whether these differences in means are driven by a few high WTP estimates. In this analysis of median WTP estimates, we find the same trends as in the differences in means. Median WTP for the Venmo group (\$0.70) is higher than debit (\$0.50) and credit (\$0.50). The median WTP for Venmo *Public* (\$1.00) is the highest, Venmo *Friends* (\$0.50) is the lowest, and Venmo *Private* (\$0.75) falls between the two. Priming has

a higher median WTP (\$0.75) than no priming (\$0.50). For the *Public* and *Private* groups, priming increases median WTP (\$0.63 to \$0.75 for *Private*; \$0.75 to \$1.00 for *Public*) but priming has no impact on median WTP for *Friends Only* (\$0.50 regardless of priming assignment). Given that we find the same trends in median WTP as mean WTP across treatment groups, we do not find the skewness of the WTP data to be concerning.

Table 2 gives the results of our OLS regression analyses, which we conduct to account for variation in WTP caused by differences across the ten items. Column (1) contains the estimates of a basic OLS regression with item-level fixed effects in which indicators for the credit and Venmo treatments (excluding debit) are regressed against willingness to pay. The specification in column (2) includes controls for Venmo usage. Columns (3) and (4) repeat the same specifications as (1) and (2) but replace the single Venmo indicator with an indicator for each of the three privacy setting assignments. Columns (5) and (6) replace the privacy setting variables with six indicators, one for each combination of privacy setting and priming assignment; column (6) is the regression estimation we described in the experimental design section. Column (7) contains the estimate of a OLS regression with item-level fixed effects in which an indicator for the priming treatment is regressed against willingness to pay. Column (8) repeats the same specification with controls for Venmo usage.

Each of these specifications addresses a different hypothesis regarding the Venmo Effect. For the general Venmo Effect, Column (2) shows that Venmo increases mean WTP by \$0.02 in comparison to debit while credit decreases mean WTP by \$0.11, though these coefficients are not statistically significant at the 5% level. For the mental accounting mechanism, Column (6) finds that the *Venmo Private No Priming* treatment has a statistically insignificant \$0.02 lower WTP than the debit group. For the signaling mechanism, Column

Table 2: Main Results -- The Effect of Payment Form on Willingness to Pay

VARIABLES	(1) WTP	(2) WTP	(3) WTP	(4) WTP	(5) WTP	(6) WTP	(7) WTP	(8) WTP
<i>Payment Forms (Debit omitted)</i>								
Credit Card	-0.113*	-0.113	-0.113*	-0.114	-0.113*	-0.115		
	[0.051]	[0.096]	[0.051]	[0.096]	[0.051]	[0.096]		
Venmo	0.0566	0.0230						
	[0.055]	[0.069]						
<i>Venmo Privacy Settings</i>								
Venmo Private			0.0832	0.0657				
			[0.077]	[0.088]				
Venmo Friends			-0.160***	-0.160**				
			[0.036]	[0.079]				
Venmo Public			0.265**	0.180**				
			[0.092]	[0.091]				
<i>Venmo Treatment Groups</i>								
Venmo Private No Priming					-0.00967	-0.0197		
					[0.108]	[0.101]		
Venmo Private Priming					0.198**	0.179		
					[0.083]	[0.122]		
Venmo Friends No Priming					-0.0714	-0.0508		
					[0.046]	[0.098]		
Venmo Friends Priming					-0.277***	-0.299***		
					[0.062]	[0.092]		
Venmo Public No Priming					0.0420	0.0454		
					[0.071]	[0.114]		
Venmo Public Priming					0.462***	0.289**		
					[0.125]	[0.116]		
<i>Priming Treatment</i>								
Priming							0.159***	0.103
							[0.036]	[0.077]
Constant	1.068***	1.182***	1.068***	1.185***	1.068***	1.151***	1.050***	1.130***
	[0.039]	[0.107]	[0.039]	[0.107]	[0.039]	[0.107]	[0.017]	[0.124]
Item-Level FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	2,339	2,289	2,339	2,289	2,339	2,289	1,509	1,459
R-squared	0.002	0.010	0.013	0.017	0.021	0.021	0.003	0.022

Note: This table shows the results of our regression estimations. The outcome variable is mean WTP indicated by participants and each of the variables is a binary indicator for whether the participant was assigned to that treatment group. The Debit indicator is omitted, meaning the constants for columns (1), (3), and (5) should be interpreted as the difference between mean WTP for debit and mean WTP for that respective treatment group. Columns (7) and (8) are limited to participants assigned to Venmo; the constant in column (7) is the mean WTP for participants assigned to Venmo without priming. Columns (2), (4), (6), and (8) include controls for Venmo usage variables, specifically age of account, number of friends, number of linked payments, percentage of spend via Venmo, monthly transactions, monthly inflow, and monthly outflow. All coefficients are nearly identical without fixed effects and exactly identical with additional individual-level fixed effects.

(4) estimates coefficients for each of the Venmo privacy settings; we find that the *Public* privacy setting increases mean WTP by \$0.18, the *Private* setting increases mean WTP by \$0.07 (though not at a statistically significant level), and the *Friends* privacy setting decreases mean WTP by \$0.16. Wald postestimation tests show that the coefficients for each of the privacy settings statistically differ from each other at the 1% level. For the priming

mechanism, Column (8) finds that the priming treatment increases mean WTP by \$0.10. Additionally, Column (6) allows us to examine the effect of priming within each privacy setting. The *Friends* setting has a larger decrease in WTP when paired with priming and the *Public* and *Private* settings have larger increases in WTP when paired with priming. Wald postestimation tests find that the coefficients between the priming and no priming treatment groups differ significantly for *Friends* (Prob > F = 0.0213) and *Public* (Prob > F = 0.0830), but not for *Private* (Prob > F = 0.1468).

6.3 Results by Item Type

As Venmo is typically used for specific types of purchases, like food and drinks, we also investigate whether the impact of payment form depends on the type of item being purchased. We divide the ten items in our experiment into four categories: *Food/Drinks* (the can of Coca Cola, granola bar, pack of gum, and bottle of coffee), *Office Supplies* (the notebook, pen, and phone wallet), *Toiletries* (the toothpaste and soap), and *COVID-Related Items* (the cloth face mask). Table 3 shows the results of the fixed effects regressions we run. Column (1) contains the estimates of a basic OLS regression with dummy variables for the item categories, omitting the *Food/Drinks* category. While all the coefficients are statistically significant, it could be argued that these differences in willingness to pay are simply reflections of the different items' values. Column (2) adds variables for seven of the eight treatment groups, omitting debit. Column (3) adds interaction terms between the treatment groups and the item categories; again, the debit and *Food/Drink* groups are omitted to avoid multicollinearity. In examining the estimates of (3), we find little evidence that the *Venmo Effect* depends on the type of item purchased. The only statistically significant interaction variable is for *Venmo Private No Priming * COVID*, which means that the mean WTP for

Table 3: Willingness to Pay by Type of Item

VARIABLES	(1) WTP	(2) WTP	(3) WTP
<i>Categories (Food/Drinks omitted)</i>			
Office Items	0.175*** [0.065]	0.175*** [0.065]	0.181 [0.133]
Toiletry Items	0.504*** [0.075]	0.504*** [0.074]	0.490*** [0.156]
COVID-Related Items	0.760*** [0.129]	0.761*** [0.128]	0.965*** [0.246]
<i>Treatment Groups (Debit omitted)</i>			
Credit Card		-0.113 [0.093]	0.000473 [0.110]
Venmo Private No Priming		-0.00967 [0.100]	0.0911 [0.130]
Venmo Private Priming		0.198* [0.117]	0.149 [0.155]
Venmo Friends No Priming		-0.0714 [0.094]	-0.0675 [0.115]
Venmo Friends Priming		-0.277*** [0.087]	-0.246** [0.105]
Venmo Public No Priming		0.0420 [0.103]	0.0267 [0.130]
Venmo Public Priming		0.462*** [0.122]	0.411*** [0.153]
<i>Interaction Terms</i>			
CreditCard * Office			-0.156 [0.194]
Venmo Private No Priming * Office			-0.0323 [0.239]
Venmo Private Priming * Office			0.0632 [0.283]
Venmo Friends No Priming * Office			0.0623 [0.214]
Venmo Friends Priming * Office			-0.0973 [0.191]
Venmo Public No Priming * Office			-0.0195 [0.243]
Venmo Public Priming * Office			0.154 [0.301]
Credit Card * Toiletry			-0.218 [0.230]
Venmo Private No Priming * Toiletry			-0.0149 [0.283]
Venmo Private Priming * Toiletry			0.0451 [0.301]
Venmo Friends No Priming * Toiletry			-0.0631 [0.236]
Venmo Friends Priming * Toiletry			0.146 [0.261]
Venmo Public No Priming * Toiletry			0.132 [0.291]
Venmo Public Priming * Toiletry			0.211 [0.317]
Credit Card * COVID			-0.231 [0.535]
Venmo Private No Priming * COVID			-0.881** [0.349]
Venmo Private Priming * COVID			0.222 [0.496]
Venmo Friends No Priming * COVID			-0.0998 [0.472]
Venmo Friends Priming * COVID			-0.303 [0.379]
Venmo Public No Priming * COVID			-0.0520 [0.417]
Venmo Public Priming * COVID			-0.372 [0.469]
Constant	0.859*** [0.035]	0.839*** [0.062]	0.819*** [0.074]
Observations	2,339	2,339	2,339
R-squared	0.034	0.053	0.059

Note: Note: This table shows the results of our regression estimations by type of item. The outcome variable is mean WTP indicated by participants. The category variables are binary indicators for whether the item is from that category. The treatment group variables are binary indicators for whether the participant was assigned to that treatment group. The interaction terms are simple interaction variables between the categories and the treatment groups.

COVID-Related Items when using the *Venmo Private* setting without priming is \$0.88 less than the mean WTP for items in the *Food/Drinks* category when using a debit card, approximately a 100% decrease. Wald tests within each category do not find significant differences in coefficients for each of the seven payment groups.

6.4 Discussion

Our difference in means analysis finds that a *Venmo Effect* exists as participants had higher willingness to pay estimates with Venmo than with credit or debit cards, though the corresponding coefficient in our regression estimation is not statistically significant. We are not particularly concerned by the lack of statistical significance as we believe it is a function of sample size limitations.

As expected, we find that priming overall increases willingness to pay when using Venmo. However, for the *Friends* privacy setting, we find that priming actually decreases WTP. In contrast, priming increases WTP for the *Private* and *Public* settings. In the absence of priming, the *Friends* treatment decreases WTP while the *Private* and *Public* treatments increase WTP. Thus, the priming treatment heightens any existing influences on WTP like the privacy settings rather than having a uniformly positive effect on its own.

This finding that the Venmo *Friends* treatment had a lower mean WTP than debit or the other Venmo privacy settings is inconsistent with our initial hypothesis about the signaling mechanism. This seems to suggest that spending money on Venmo is shameful, rather than a positive signal of wealth or social status as we had expected. This could be a result of the specific experimental context, since participants knew that they would have to pay a third party Venmo account named “Willingness to Pay Research.” College students may be embarrassed to show their peers that they made a Venmo payment as a part of an

experiment; they could be concerned that paying a stranger makes them seem naïve to their peers or that participating in research makes it seem as if they are in need of money. While this result is the opposite direction of what we expected, it shows that the privacy setting on Venmo does have an impact on willingness to pay, reinforcing the importance of Venmo's social factors on spending.

Surprisingly, we find that credit cards yield lower WTP estimates than debit cards. This challenges the existing literature (Hirschman 1979; Feinberg 1986) that finds higher willingness to pay with credit than debit. This unexpected finding may suggest a generational change; today's youth may feel less comfortable with credit (or the accrual of interest) than their parents and grandparents. It could also simply be a factor of inexperience due to the young age of our participants. Given that 98% of participants have a debit card but only 72% have a credit card, we test whether this difference in ownership is driving the WTP gap by limiting the sample to participants who have both a debit and credit card. In this analysis, we find that credit cards yield a \$0.16 (s.e. (\$0.067)) lower mean WTP than debit cards, a larger and more statistically significant effect than those found in our regression estimations with the full sample (see Table 2). This suggests that the difference in WTP between debit and credit is not driven by a lack of owning credit cards. Although the difference in WTP cannot be attributed to differential credit card possession, it could be a result of the length of time that participants have had their credit and debit cards. We do not have data on length of possession, but most participants have probably had a credit card at most for a few years, which could mean that they are less familiar with credit than debit and are thus more hesitant to spend with credit.

7. Conclusion

This paper is the first study to examine the impact of a specific digital payment platform on consumer willingness to pay, building on existing literature about the role of payment form in consumer spending decisions. We find evidence that a *Venmo Effect* – a higher willingness to pay with Venmo – exists in college students’ spending behavior. This is an important expansion of our understanding of the role of context effects in economic choice. More specifically, we find that Venmo increases WTP in comparison to debit or credit cards, though not statistically significantly. In our exploration of three potential mechanisms behind this *Venmo Effect*, we find evidence of two specific social influences on WTP with Venmo: 1) the *Friends Only* privacy setting decreases WTP while the *Public* privacy setting increases WTP, at least in this particular experimental context, and 2) browsing the social feeds exacerbates the effect of privacy setting, regardless of whether that causes an increase or decrease in WTP.

These findings have important implications for Venmo users, retailers, and Venmo itself. First, the *Venmo Effect* is causing consumers to spend more money than they would with another form of payment. This is an important discovery as Venmo users seem to be unaware of this phenomenon; surveyed Venmo users claimed that they are not influenced to purchase goods on Venmo by others’ transactions (Caraway et al. 2017). Given that we find the *Venmo Effect* to be driven by social influences rather than mental accounting, consumers who want to avoid this *Venmo Effect* could: 1) avoid the social feeds on the Venmo app if using the *Private* or *Public* settings, as we found that the priming treatment increased WTP, or 2) change the default privacy setting to *Friends Only* because it led to lower WTP than the *Private* or *Public* settings and even debit cards. On the other hand, retailers could take

advantage of the *Venmo Effect* in order to increase profits. While more retailers have begun to accept Venmo in recent years, it is far from a universal option. By accepting Venmo, retailers would be able to make more money without needing to expand their customer base. Venmo's seller fee structure (1.9% of the transaction value + \$0.10) is similar to that of credit card companies, so retailers could capture the full increase in WTP at the same cost as other payments with lower associated consumer WTPs.

Venmo, which is owned by PayPal, makes money through the transaction fees it charges on payments made via credit card and on instant bank transfers. Thus, Venmo's revenue is tied to payment volume, which already benefits from the existence of the *Venmo Effect*. However, Venmo could attempt to maximize the impacts of the *Venmo Effect* through the privacy settings and the social feeds (i.e., the signaling and priming mechanisms). Our findings suggest that Venmo could increase payment volume if more users were on the *Public* or *Private* settings; the current default privacy setting on the Venmo app is *Public*, but disincentivizing or even eliminating the *Friends Only* setting could lead to more spending on Venmo. Additionally, given our finding that browsing the social feeds leads to higher levels of spending, Venmo could attempt to increase traffic on the social feeds.

While we are confident in our findings of a *Venmo Effect*, we recognize that more in-depth study of Venmo is needed. There are three particular extensions that we think should be prioritized. First, this experiment was conducted completely online, which is not fully representative of Venmo transactions as many people may use Venmo when they're physically with their friends or in a more traditional retail setting. Thus, exploring how this *Venmo Effect* translates to an in-person experiment is of interest. Second, we recognize that the specific context of our experiment could be responsible for our finding that the *Friends*

Only setting decreases WTP; paying a third-party experimental Venmo account for a bar of soap does not have the same social implications as, say, paying a well-regarded peer for a transaction that would be regarded as “cool” by others. Modifying the experimental design so participants would pay a friend – or at least a decoy account that participants believe belongs to a peer – would allow us to determine whether the *Friends* setting has a general downwards effect or if our findings are only applicable to this specific experimental context. Third, our experiment only examines the *Venmo Effect* for low-cost consumer products. Existing literature finds that the credit card premium increases with the value of the item being purchased (Prelec and Simester 2001), and the effect of Venmo on WTP could similarly increase at higher prices. Alternately, the *Venmo Effect* could disappear at higher prices as Venmo is commonly used for smaller purchases. We look forward to better understanding this novel finding about the role of digital payment platforms on consumer spending, especially as digital payments continue to grow in popularity.

8. Appendix

8.1 Tables and Figures

APPENDIX TABLE 1: Pairwise t-tests of the summary statistics presented in Table 1 (page 28).

Appendix Table 1: Pairwise T-Test Values for Summary Statistics Across Treatment Groups

	(Credit - (Debit))		(Credit - (Vemo Friends No Printing))		(Credit - (Vemo Friends No Printing))		(Credit - (Vemo Friends No Printing))		(Credit - (Vemo Friends No Printing))		(Credit - (Vemo Friends No Printing))		(Credit - (Vemo Friends No Printing))		(Credit - (Vemo Friends No Printing))		(Credit - (Vemo Friends No Printing))		(Credit - (Vemo Friends No Printing))									
	(Credit - (Debit))	(Vemo Friends No Printing)	(Credit - (Vemo Friends No Printing))	(Vemo Friends No Printing)	(Credit - (Vemo Friends No Printing))	(Vemo Friends No Printing)	(Credit - (Vemo Friends No Printing))	(Vemo Friends No Printing)	(Credit - (Vemo Friends No Printing))	(Vemo Friends No Printing)	(Credit - (Vemo Friends No Printing))	(Vemo Friends No Printing)	(Credit - (Vemo Friends No Printing))	(Vemo Friends No Printing)	(Credit - (Vemo Friends No Printing))	(Vemo Friends No Printing)	(Credit - (Vemo Friends No Printing))	(Vemo Friends No Printing)	(Credit - (Vemo Friends No Printing))	(Vemo Friends No Printing)								
Demographic Variables																												
Age	0.244	0.202	0.515	0.524	0.337	-0.054	0.386	-0.042	0.271	0.280	0.093	-0.278	0.142	0.313	0.322	0.135	-0.236	0.184	0.009	-0.178	-0.549	-0.129	-0.187	-0.558	-0.138	-0.371	0.048	0.420
Year Of Study	0.018	0.128	0.394	0.394	0.062	-0.117	0.142	0.090	0.356	0.353	0.024	-0.155	0.105	0.266	0.263	-0.066	-0.245	0.014	-0.003	-0.332	-0.511	-0.252	-0.329	-0.508	-0.249	-0.179	0.080	0.260
Female	-0.155	-0.121	0.045	-0.255**	-0.063	0.004	0.007	0.033	0.200	-0.100	0.091	0.158	0.162	0.167	-0.133	0.058	0.125	0.128	-0.300**	-0.109	-0.042	-0.038	0.191	0.258**	0.262**	0.067	0.070	0.003
White	0.178*	0.040	0.318**	0.185	0.079	0.110	0.126	-0.138	0.140	0.007	-0.099	-0.068	-0.052	0.278**	0.144	0.039	0.069	0.085	-0.133	-0.239	-0.208	-0.192	-0.106	-0.075	-0.059	0.031	0.047	0.016
Household Income	-0.241	0.239	0.330	-0.575	0.009	-0.289	-0.198	0.480	0.571	-0.333	-0.333	0.250	-0.048	0.091	-0.813	-0.230	-0.258	-0.437	-0.905**	-0.321	-0.619	-0.538	0.583	0.286	0.377	-0.298	-0.207	0.091
Vemo Usage																												
Vemo Balance	64.273	107.233	7.366	98.252	-6.692	66.085	41.979	42.860	-56.907	34.979	-70.965	1.811	-22.294	-98.867**	-7.981	-113.925	-41.149	-65.255	91.886*	-14.058	58.718	34.612	-105.945	-33.168	-57.274	72.777	48.671	-24.106
Years with Vemo Account	-0.110	-0.401	0.398	0.246	0.061	-0.090	0.162	-0.290	0.509	0.356	0.171	0.080	0.272	0.799**	0.646*	0.370	0.663	-0.153	-0.338	-0.429	-0.236	-0.185	-0.276	-0.084	-0.091	0.101	0.192	
Number of Friends on Vemo App	7.542	-5.226	24.455	35.182*	-31.340	-1.527	-8.484	-12.767	16.913	27.640*	-38.882*	-9.068	-15.975	29.680	40.407**	-26.114	3.699	-3.208	10.727	-55.794*	-25.981	-32.888	-66.522**	-36.708*	-41.615**	29.813	22.906	-6.907
Vemo Transactions Per Month	2.252	2.044	2.992	1.703	0.709	2.178	1.700	-0.308	0.241	-0.549	-1.545**	-0.074	-0.551	0.949*	-0.341	-1.335	0.134	-0.343	-1.289	-2.284**	-0.814	-1.292*	-0.994	0.475	-0.003	1.469	0.992	-0.478
Percentage of Money Spent via Vemo	-1.681	-2.253	-4.985	-4.630*	-8.943**	-2.259	-4.357	-0.571	-3.304	-2.949	-7.262*	-0.578	-2.732	-2.378	-6.691	-0.007	-2.105	-0.007	-2.105	-3.958	2.725	0.628	-4.313	2.371	0.273	6.684	4.586	-2.098
Social Media Usage																												
Number Of Social Media Sites Used	0.003	-0.104	0.530	0.570	0.576	0.511	0.803	-0.107	0.527	0.567	0.573	0.508	0.800*	0.635	0.674	0.680	0.616	0.907	0.039	-0.019	0.164	0.273	0.006	-0.058	0.233	-0.064	0.227	0.292
Average Number of Hours Spent on Social Media Per Day	-0.061	0.086	-0.250	0.197	0.090	-0.355	0.136	0.147	-0.189	0.258	0.151	-0.294	-0.075	-0.336	0.111	0.004	-0.441	-0.222	0.447	-0.105	0.016	0.114	-0.107	-0.552	-0.333	-0.445	-0.226	0.219
WTP Estimates																												
Average WTP for All Items	-0.113	-0.103	-0.757*	-0.041	0.164	-0.155	-0.575**	0.010	-0.644*	0.071	0.277	-0.042	-0.462*	-0.654	0.062	0.287	-0.052	-0.472	0.715	0.921*	0.602	0.182	0.205	-0.113	-0.534*	-0.318	-0.739**	-0.420
Average WTP for Food or Drink Items	0.000	-0.091	-0.149	0.068	0.247	-0.026	-0.411*	-0.091	-0.149	0.068	0.246	-0.027	-0.411*	-0.058	0.159	0.337*	0.064	-0.320	0.217	0.395**	0.122	-0.262	0.179	-0.094	-0.479**	-0.273	-0.657**	-0.384
Average WTP for Office Supply Items	-0.155	-0.214	-0.367	-0.150	0.188	-0.162	-0.720**	-0.059	-0.212	0.065	0.344	-0.007	-0.565*	-0.154	0.064	0.402	0.052	-0.566	0.218	0.556*	0.205	-0.352	0.338	-0.012	-0.570	-0.351	-0.908**	-0.558
Average WTP for Toiletry Items	-0.054	-0.073	-0.103	-0.022	-0.029	-0.094	-0.210**	-0.019	-0.049	0.033	0.025	-0.040	-0.155*	-0.029	0.052	0.044	-0.021	-0.136	0.081	0.074	0.009	-0.107	-0.008	-0.072	-0.188**	-0.065	-0.180*	-0.116
Average WTP for COVID-Related Items	-0.231	0.559	-5.049	-0.063	0.319	-0.205	-0.270	0.790**	-4.818	0.167	0.550	0.025	-0.039	-5.608	-0.622	-0.240	-0.764*	-0.829*	4.986	5.368	4.844	4.779	0.382	-0.142	-0.206	-0.524	-0.589	-0.064

The value displayed for t-tests are the differences in the means across the groups.

*, **, and *** denote significance at the 10, 5, and 1 percent critical level.

Note: This table displays pairwise t-test statistics shown in Table 1 in the Results section. For mean values, standard errors, and sample size of each group, see Table 1 in the Results section.

Household income is categorical; 0 represents income under \$20,000, 1 represents \$20,000-\$34,999, 2 represents \$35,000-\$49,999, 3 represents \$50,000-\$74,999, 4 represents \$75,000-\$99,999, and 5 represents \$100,000+.

8.2 Survey Interface

FIGURE 1: An informed consent form is the first page of the experiment. This is followed by screening questions about age, college attendance, Venmo usage, and debit/credit card possession.

Welcome to the survey! Thank you in advance for your participation in my senior thesis project.

This survey should only be taken on a computer. You will need to use your phone during the survey, so please have it accessible.

Purpose: The purpose of this research is to measure how different factors impact consumer willingness to pay. This study is part of a senior thesis project for the economics department at Amherst College.

Participation: Participation in this study will involve answering questions about how much you are willing to pay for various consumer goods as well as questions about the goods themselves. Based on your indicated willingness to pay, you will have the opportunity to purchase items that you may want to buy. If you purchase any item, we will ship it to you for free. You will purchase at most one item, which will cost you less than \$5. The survey first asks a series of qualifying questions, which should take about 10 minutes. If you qualify for the survey, the remaining questions should take 20 to 30 minutes to complete.

Risks: There are no known risks associated with participating in this study other than those associated with regular online activity like online shopping.

Compensation: If you qualify for the survey, you will receive a \$5 Amazon gift card via email within 24 hours. Each participant will only be compensated once; you will not receive another gift card if you submit the survey twice.

Confidentiality: Only researchers involved with the study will have access to the information you provide. Credit/debit card information will be collected through Square, a third party service, so researchers will not have access to this data. Any public report we make related to this survey will not include any information that would make it possible to identify you.

Voluntary Participation: Participation in this study is completely voluntary, so you may decline to participate or decide to end your participation at any time for any reason.

Questions: If you have any questions, please ask the researcher conducting this study: Emily Kiernan, who can be contacted at ekiernan21@amherst.edu. If you do not have any questions and agree to participate, please select "Yes" as your answer to the below question. If you have any questions or concerns regarding your rights as a subject in this study, you may contact the Amherst College Institutional Review Board (IRB).

Do you consent to participating in this survey?

Yes

No

0% 100%

FIGURE 2: After the screening questions, participants are assigned to one of three payment forms: debit, credit, or Venmo.

Please note that we will only be able to accept payments via Venmo.

Knowing that you will be using Venmo for any later transactions, do you still want to proceed with the survey?

Yes

No

0% 100%

FIGURE 3: Those assigned to Venmo are then asked to change their default privacy setting to their randomly assigned setting of either *Private*, *Friends Only*, or *Public*.

Now, please open the Venmo app again and set your privacy settings to **Private**. For the rest of the survey, please keep your account on this setting. Once the survey is over, you may change the privacy settings to whatever you prefer.

As a reminder, you can change your privacy settings by opening the Venmo app, clicking the three parallel lines in the top right, then selecting settings, and then choosing "Privacy" under the "Preferences" heading.

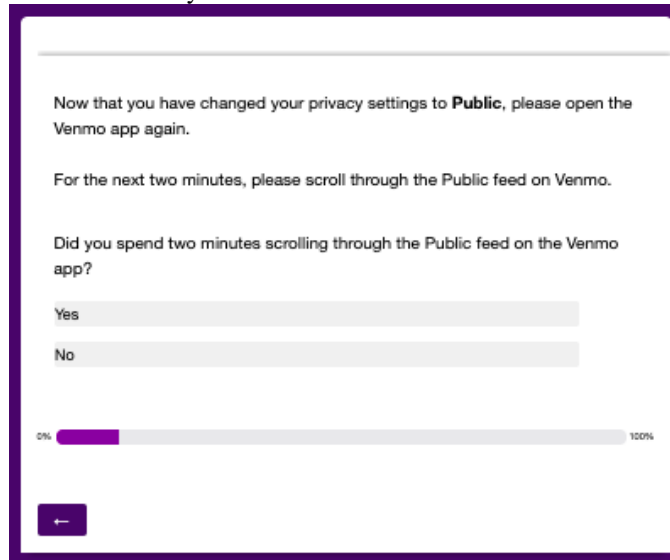
Are you willing to proceed with the survey on the **Private** setting?

Yes

No

0% 100%

FIGURE 4: Participants assigned to Venmo are then randomly assigned to either priming or no priming. Those assigned to priming are asked to scroll through the *Public* Venmo feed for two minutes while those not assigned to priming simply proceed with the survey.



Now that you have changed your privacy settings to **Public**, please open the Venmo app again.

For the next two minutes, please scroll through the Public feed on Venmo.

Did you spend two minutes scrolling through the Public feed on the Venmo app?

Yes

No


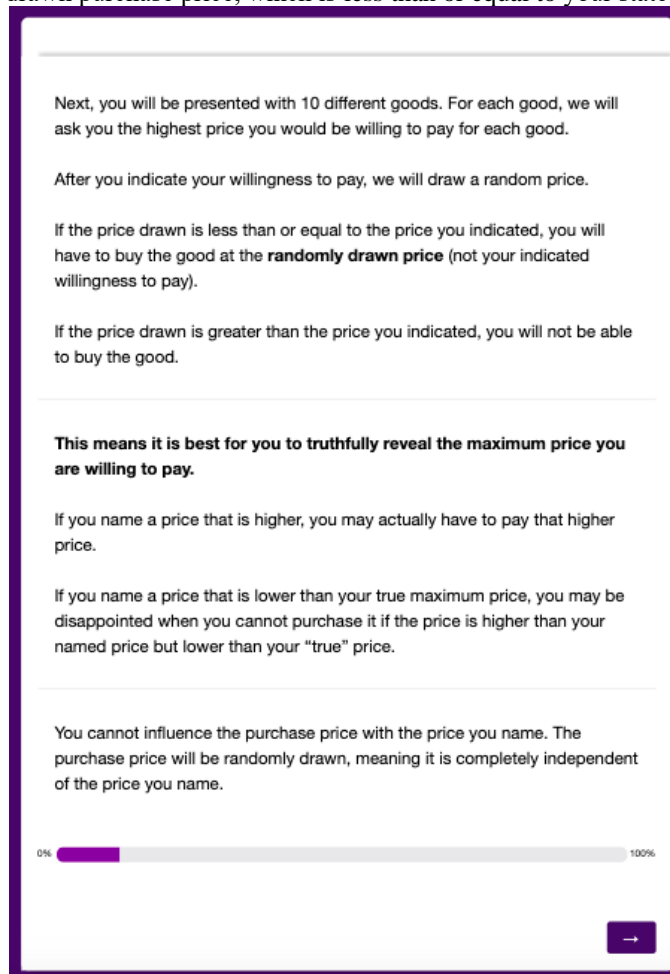
0%  100%

FIGURE 5: Next, the BDM lotteries are explained. A subsequent attention check question ensures participants understand how the lotteries work: “If you win the lottery, what is the price you will have to pay?” (Correct answer: “The randomly drawn purchase price, which is less than or equal to your stated maximum price.”)



Next, you will be presented with 10 different goods. For each good, we will ask you the highest price you would be willing to pay for each good.

After you indicate your willingness to pay, we will draw a random price.

If the price drawn is less than or equal to the price you indicated, you will have to buy the good at the **randomly drawn price** (not your indicated willingness to pay).

If the price drawn is greater than the price you indicated, you will not be able to buy the good.

This means it is best for you to truthfully reveal the maximum price you are willing to pay.

If you name a price that is higher, you may actually have to pay that higher price.

If you name a price that is lower than your true maximum price, you may be disappointed when you cannot purchase it if the price is higher than your named price but lower than your “true” price.

You cannot influence the purchase price with the price you name. The purchase price will be randomly drawn, meaning it is completely independent of the price you name.

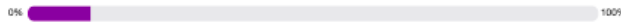
0%  100%

FIGURE 6: After participants confirm that they understand the BDM lottery process, they are told a maximum of one item will be purchased. This is followed by an attention check question: “What is the maximum number of goods you will be required to purchase?” (Correct answer: 1)

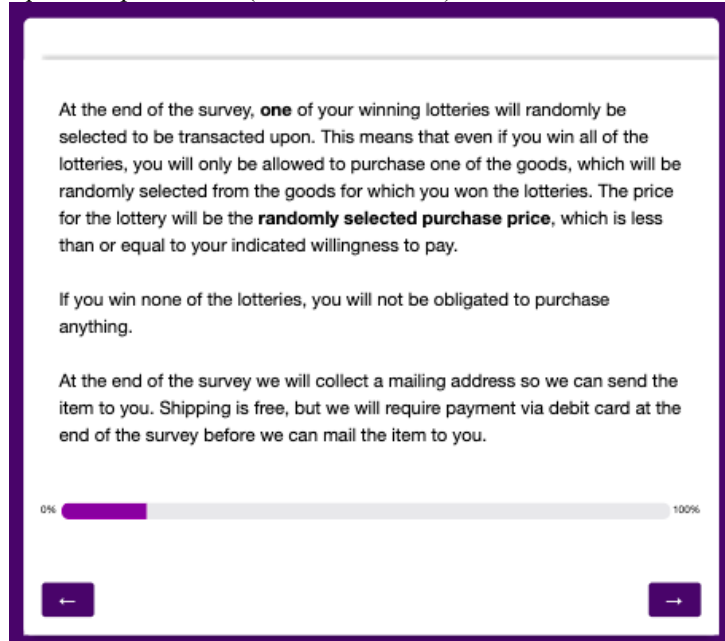


FIGURE 7: Once participants understand how the lotteries work, they are asked to name their maximum price for each of the ten items. This example shows the WTP elicitation for the pack of gum. The order of the ten items is randomized for each participant.

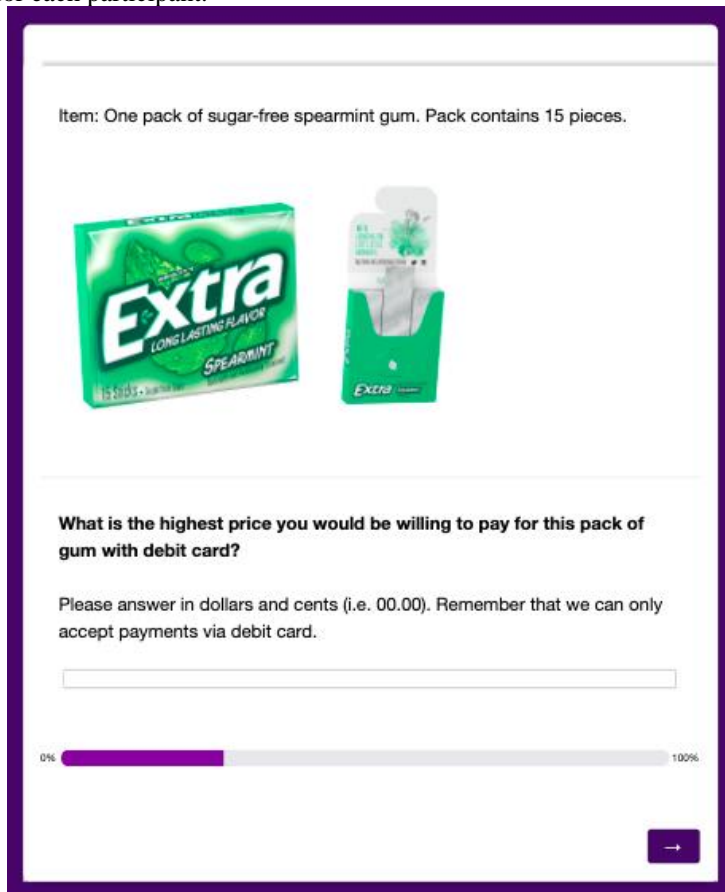


FIGURE 8: After the initial WTP estimate for each of the ten items, participants are given the option to revise their indicated maximum price.

After this, we will randomly draw a price and you will have to buy the pack of gum if the randomly drawn price is less than or equal to the price you just stated. However, if the randomly drawn price exceeds the price you just stated, you will not be able to buy the pack of gum.

Would you like to revise your maximum price?

Yes

No

0% 100%

← →

FIGURE 9: After participants indicate their WTP for a given item (regardless of whether they chose to revise), we ask follow-up questions regarding their preferences about the item.

We now have a few additional questions about this phone wallet.

Have you ever purchased a phone wallet like this before?

Yes

Unsure

No

On a scale of 0 to 10, where 0 is not at all and 10 is extremely strongly, how much do you like this item?

Dislike a great deal	Dislike a moderate amount	Dislike a little	Neither like nor dislike	Like a little	Like a moderate amount	Like a great deal				
0	1	2	3	4	5	6	7	8	9	10

How much do you like this phone wallet?

Please share any additional comments you have about this item. (Optional)

Thank you. Please click next to proceed to the next item.

0% 100%

← →

FIGURE 10: After completing the WTP estimates and follow-up questions for all ten items, a random price between \$1 and \$5 is selected for each item.

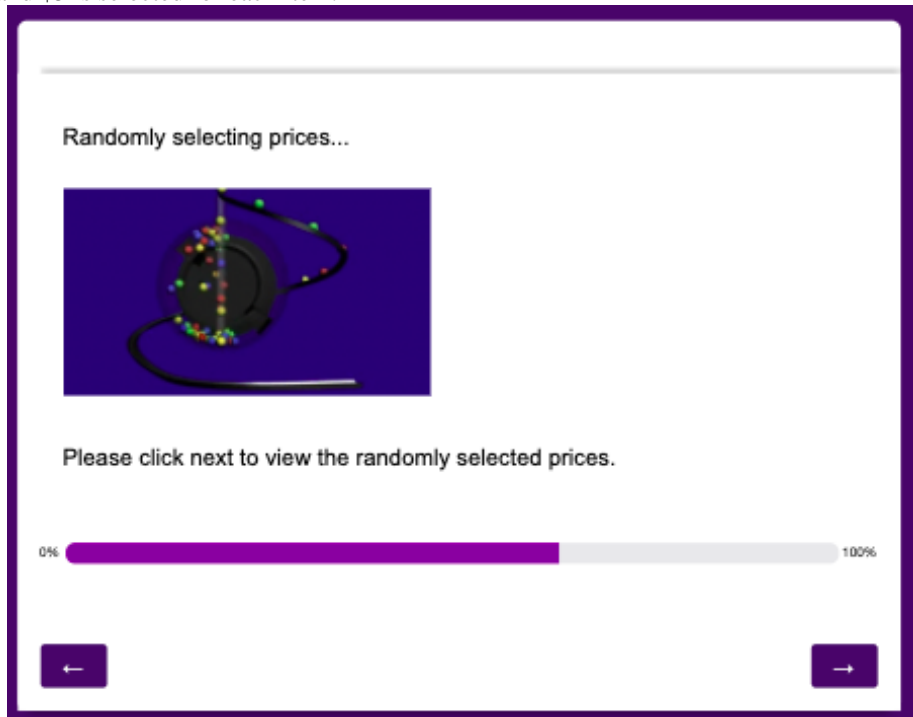


FIGURE 11: Participants are shown a summary of the ten random prices.

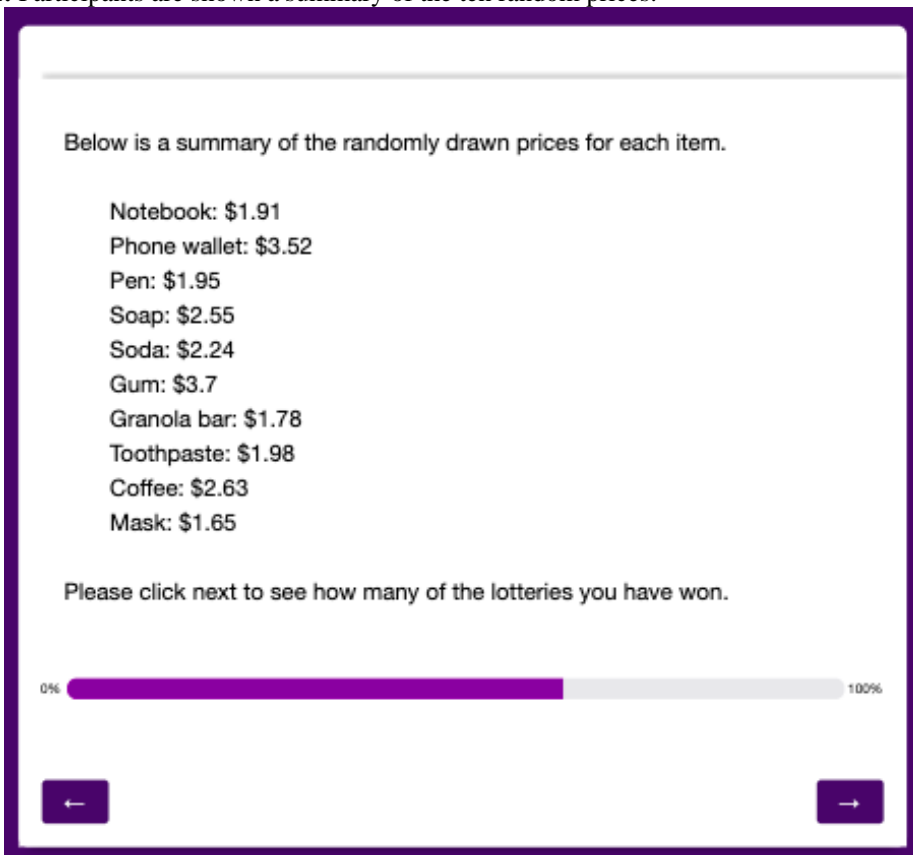



FIGURE 12: After the random selection of prices, participants are shown a table that summarizes the random prices, their indicated WTP for each item, and whether they won each lottery. Participants who won one lottery are asked to purchase that item and participants who won multiple lotteries are asked to purchase one item randomly selected from all their winning items. Participants who won zero lotteries just proceed to the final demographic questions.

Below is a summary of the ten lotteries and their outcomes.

Item	Lottery Result	Your Indicated WTP	Randomly Drawn Price
Notebook	Lost	\$0	\$1.91
Phone	Won	\$300	\$3.52
Wallet	Won	\$300	\$3.52
Pen	Lost	\$0	\$1.95
Soap	Lost	\$0	\$2.55
Soda	Lost	\$0	\$2.24
Gum	Lost	\$2	\$3.7
Granola Bar	Lost	\$0	\$1.78
Toothpaste	Lost	\$0	\$1.98
Coffee	Lost	\$2	\$2.63
Mask	Lost	\$0	\$1.65

You have won 1 of the lotteries.

As you only won one lottery, you will now purchase that item. Please click next to proceed to the payment stage.

0%  100%




 



FIGURE 13: The final page of the survey debriefs participants. All participants, regardless of whether they purchased an item, receive a \$5 Amazon e-gift card within 24 hours of completing the experiment.

This survey is intended to measure how consumer willingness to pay varies across different forms of payment. If you would like to receive a copy of the results when they are available, contact Emily Kiernan at ekiernan21@amherst.edu.

Thank you again for your participation!

Please click next to submit your response. Once you submit, you will receive your \$5 Amazon e-gift card within 24 hours.

0%  100%

8.3 References

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