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Beating Irrationality: Does Delegating to IT Alleviate the Sunk Cost Effect?

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We investigate the impact of delegating decision making to information technology (IT) on an important human decision bias—the sunk cost effect. To address our research question, we use a unique data set containing actual market transaction data for approximately 7,000 pay-per-bid auctions. In contrast with the laboratory experiments of previous related studies, our research presents the unique advantage of investigating the effects of IT-enabled automated bidding agents on the occurrence of a decision bias in real market transactions. We identify normatively irrational decision scenarios and analyze consumer behavior in these situations. Our findings show that participants with a higher behavioral investment are more likely to violate the assumption of normative economic rationality because of the sunk cost effect. More importantly, we observe that the delegation of auction participation, i.e., actual bidding, to IT significantly reduces the occurrence of the sunk cost effect in subsequent decisions made by the same individual. We can attribute this reduction to the comparably lower behavioral investments incurred by auction participants who delegate their bidding to IT. In particular, by mitigating different contributors of behavioral investments, delegating to IT reduces the likelihood of the occurrence of the sunk cost effect by more than 50%.

Keywords: Internet markets; delegating to IT; sunk cost effect; economics of automated agents; decision support systems; decision bias

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1. Introduction

One of philosophy's oldest paradoxes is the apparent contradiction between the great triumphs and the dramatic failures of the human mind. The same organism that routinely solves inferential problems too subtle and complex for the mightiest computers often makes errors in the simplest of judgments about everyday events.

(Nisbett and Ross 1980, p. xi)

We're wondering what a world looks like when there are a billion of these software agents transacting business on our behalf.

—Dr. Steve R. White, IBM Research (Chang 2002)

Over the last decade, the role of information technology (IT) has evolved from a mere decision aid to a decision-making artifact. Accordingly, IT is nowadays harnessed not only to support decision makers but also to make decisions on behalf of their owners (e.g., Chang 2002). Examples of these technologies include options for involving automated agents for bidding in online auctions (Adomavicius et al. 2009) or for trading in financial markets (Hendershott et al. 2011). Today, these agents are available at negligible marginal cost and can effectively act on behalf of their owners.

In 2009, for instance, an astonishing 73% of all equity trading volume in the United States was executed by electronic agents (Mackenzie 2009). In the wake of this development, a significant literature has emerged, analyzing the design of these software agents, their performance in real market situations, and their effect on market outcomes (e.g., Guo et al. 2012, Hinz et al. 2011). Yet despite the widespread adoption of such agents, their impact on decision making remains little understood; in other words, the effect of the delegation of decision making to IT on different aspects of decision making, especially decision biases, is underresearched. Considering the economic importance of these decision biases (DellaVigna 2009), it is critical, however, to analyze the effects of the involvement of automated software agents on the occurrence of decision biases in subsequent human decision making.

Studies of decision biases have featured in the literature for decades (e.g., Kahneman and Tversky 1979, Pope and Schweitzer 2011), including both laboratory and field research (an overview can be found in DellaVigna 2009). One important challenge for researchers is to provide mechanism for analyzing

and understanding these biases, and how they can be alleviated or even avoided. Researchers from the information systems discipline have already made useful contributions to this area. Several laboratory experiments have shown that decision support systems (DSSs) are an effective tool for mitigating some of these decision biases (e.g., Bhandari et al. 2008, Lim et al. 2000, Roy and Lerch 1996). However, none of these studies have analyzed the potential impact of automated software agents—which effectively replace the human decision maker for the delegated task—on the occurrence of decision biases in subsequent human decisions. In addition, there is no evidence that the laboratory results associated with DSSs and decision biases are applicable in real market situations. This represents a real handicap for academics and practitioners because many scholars are skeptical of the transferability of lab results to the field (e.g., List 2003). Consequently, we investigate whether or not IT can indeed alleviate decision bias in real market transactions.

One common decision bias is the so-called “sunk cost effect.” This has been defined as the “greater tendency to continue an endeavor once an investment in money, effort, or time has been made” (Arkes and Blumer 1985, p. 124). The sunk cost effect typically occurs in decision situations involving a chain of decisions (e.g., software projects, investments, exploration ventures, auctions) (Kanodia et al. 1989). In many of these situations it is now possible to delegate parts of the decision making to IT (Chang 2002). Consequently, considering these two phenomena together raises the question of the impact of delegation to IT on the sunk cost effect, which both researchers and practitioners would benefit from better understanding. Having access to data from a real market setting, we were able to investigate this issue both theoretically and empirically. In particular, we focus on the following research question: *Does the delegation of decision making to IT affect the occurrence of the sunk cost effect in a subsequent human decision situation?*

More specifically, we theoretically establish and empirically validate the impact of IT on the occurrence of the sunk cost effect. We hypothesize, first, the existence of the sunk cost effect due to behavioral investments (e.g., emotional attachment, effort, and time), and second, the mitigating effect of delegating decision making to IT on behavioral investments, and hence on the likelihood of the occurrence of the sunk cost effect in subsequent human decision making. In other words, by mitigating the effect of different contributors of behavioral investment, the delegation to IT affects the likelihood of the occurrence of the sunk cost effect. Although there is anecdotal evidence for the link between delegating decision making to IT and the reduction of behavioral investments (Bapna 2003), we do not know of any paper which theoretically or

empirically investigates this issue, nor is there an in-depth understanding of the impact of *behavioral* investments on the sunk cost effect. Previous experimental studies have come up with contradictory results: some have found a positive effect of behavioral investments on the sunk cost effect (e.g., Cunha and Caldieraro 2009, 2010; Navarro and Fantino 2009), whereas others were unable to replicate these experimental results (Otto 2010), or did not find evidence for the existence of the sunk cost effect for a behavioral investment, such as time (Soman 2001).

The recent rise in online pay-per-bid auctions (e.g., Beezid.com, Bidcactus.com) has generated detailed data, which we were able to access, giving us the opportunity to test our hypotheses in a real market setting. The growth in popularity of this type of auction has attracted considerable media attention. For example, Thaler (2009) writes in the *New York Times* about one large pay-per-bid auction website: “Here, the theory [of the sunk cost effect] is employed in some diabolically inventive ways.” It is all the more fitting and advantageous, therefore, that we are able to use a unique and rich data set provided by a German website offering pay-per-bid auctions.¹ This data set includes detailed customer-level bidding and transaction data from approximately 7,000 auctions that took place between August 2009 and May 2010. Furthermore, our data set allows us to distinguish, on a bid level, whether a bid was placed manually or via an automated bidding agent, with the former likely to induce higher behavioral investments than the latter. This unique feature allows us to empirically analyze the impact of delegation to IT on the sunk cost effect on subsequent human decisions, and to verify the existence of a sunk cost effect for behavioral investments.

The decisions we analyze are normatively irrational decision scenarios of auction participants. In our empirical analysis we find that the likelihood of making an irrational decision is significantly influenced by a participant’s behavioral investment during an auction. Confirming our hypotheses, the likelihood of making an irrational decision is an increasing function of behavioral investments during a specific auction: thus, auction participations in which an individual

¹ The website provider has requested to remain anonymous. Pay-per-bid auction participation has been likened to gambling, which may raise concerns, for some, about whether decision biases should be analyzed in such a context. But even if we were to consider auction participation as a form of gambling, the decisions we analyze occurred *after* the supposed gamble. This is because an auction participant first takes part in an auction and only thereafter decides whether to exercise the direct-buy option, as our paper will explain. It is this distinct postparticipation decision that is the focus of our analysis. Nonetheless, gambling situations like poker (e.g., Smith et al. 2009), racetrack betting markets (e.g., Jullien and Salanié 2000), or lotteries (e.g., Cook and Clotfelter 1993) are widely used in the literature to analyze decision making and, especially, decision biases.

invested more time and effort are more likely to be followed by irrational decisions, compared with participations in which the same individual invested less in terms of behavioral resources. The effect of behavioral investments on the occurrence of the sunk cost effect is moderated by the usage of an automated bidding agent. We observe a substantial reduction in the occurrence of the sunk cost effect for participations where decision making is delegated to IT. This reduction is attributable to the lower behavioral investments that accrue when auction participants delegate their bidding to IT. In particular, by mitigating different contributors of behavioral investments, delegating to IT reduces the likelihood of the occurrence of the sunk cost effect by more than 50%.

This paper makes several significant contributions to the literature. First, only a few studies have so far analyzed the effects of IT usage on decision biases and, more importantly, none of these considered the sunk cost effect. To the best of our knowledge this paper is the first to explore this issue. We theoretically establish and empirically test whether, by reducing behavioral sunk costs, IT can alleviate the occurrence of the sunk cost effect and thus improve the quality of decisions. Second, the literature on decision biases and IT focuses almost exclusively on DSSs, which *support* decision makers. Considering the increasing number of opportunities where decision makers can *delegate* their decision making to automated agents, it is worth investigating the impact of these new information technologies on decision biases. Third, the impact of IT on decision biases was hitherto analyzed only in experimental settings. This is the first study that extends these results to a real market setting. Fourth, the experimental evidence on the sunk cost effect in relation to behavioral investments is very limited, and to the best of our knowledge there is no field evidence. By theoretically establishing and empirically validating the positive effect of delegation of decision making to IT, that is, decreasing the occurrence of the sunk cost effect, we provide the first field evidence for the existence of the sunk cost effect for behavioral investments. In summary, we provide new insights relevant to information systems research and behavioral economics research that will benefit practitioners and researchers alike.

2. Theory and Hypotheses

2.1. Literature Review

Two streams of research are relevant to our study. The first examines the effect of information technologies on different decision biases and tests whether and how these technologies can alleviate such biases. The second stream analyzes the sunk cost effect in different laboratory and field settings. In the following paragraphs we discuss relevant work from both of these streams.

A growing body of experimental research has examined the effect of DSSs on different kinds of human decision biases. In general, these studies have found DSSs to be an effective tool for alleviating decision biases in experimental setups. In particular, earlier studies have shown that such systems can alleviate the anchoring and adjustment bias (George et al. 2000, Hoch and Schkade 1996, Lau and Coiera 2009), the base rate bias (Hoch and Schkade 1996, Roy and Lerch 1996), the first impression bias (Lim et al. 2000), the familiarity bias (Marett and Adams 2006), the framing bias (Bhandari et al. 2008, Cheng and Wu 2010), the representativeness bias (Bhandari et al. 2008), and the ambiguity effect (Bhandari et al. 2008). To the best of our knowledge, however, no study to date has analyzed the effect of IT usage on the sunk cost effect.

Various approaches to alleviate decision biases have been proposed in the literature. In his seminal work on debiasing, Fischhoff (1982) proposed a classification of these approaches based on the source of the decision bias. He identified faulty tasks, faulty decision makers, and mismatches between decision makers and tasks as potential sources. In the case of faulty tasks, he proposed that the redesign of the task environment could debias the decision maker. If a faulty decision maker is the source of a decision bias, Fischhoff proposed an escalation design with four steps to debias the decision maker. The first step in this escalation design entails warning the decision maker about the potential for bias, the second step is to describe the bias, the third is to provide personalized feedback, and the fourth is to train the decision maker. Alternatively, the decision maker could be replaced. In case of a mismatch between the decision maker and the task, Fischhoff (1982) proposed to restructure the task in a way that renders both task and decision maker as compatible as possible. Most of the extant studies restructured the task by modifying the presentation format (Bhandari et al. 2008, Hoch and Schkade 1996, Lau and Coiera 2009, Lim et al. 2000, Roy and Lerch 1996) or by providing further information (Marett and Adams 2006), which resulted in the potential debiasing of the decision maker, whereas two other studies used warnings to debias the decision maker (Cheng and Wu 2010, George et al. 2000).

Our study extends the earlier work on IT usage and decision biases in three key ways. First, we analyze a new kind of IT that can help alleviate or even prevent decision biases. Compared to DSSs, automated software agents differ both in terms of functionality and purpose. The main purpose of a DSS is to *support* a decision maker, whereas automated software agents *act in place* of their owners. As many researchers argue that the delegation of decision making can offer an effective way for alleviating decision biases (e.g., Fischhoff 1982, Roy and Lerch 1996), and with automated software agents

providing numerous opportunities to delegate decision making, such agents are an obvious tool to alleviate or even eliminate decision biases. Nevertheless, to the best of our knowledge, none of the previous studies analyze the effect of automated software agents on decision biases in subsequent human decision making. Second, we use data obtained from a real market situation. This allows us to extend the existing work on the effects of IT usage in an important way. All of the above-mentioned studies obtain their results from laboratory experiments. Therefore, it is important to extend the experimental results to field settings. Third, we study the impact of IT usage on the sunk cost effect. Although the sunk cost effect has important economic implications, it has not yet been analyzed in the context of IT usage and decision biases.

The second relevant stream of literature for our research addresses the sunk cost effect. Thaler (1980, p. 47) provides the following example for this effect: "A family pays \$40 for tickets to a basketball game to be played 60 miles from their home. On the day of the game there is a snowstorm. They decide to go anyway, but note in passing that had the tickets been given to them, they would have stayed home." Standard economic theory predicts that, regardless of whether the family paid for the tickets or received them for free, this should not influence their decision to go to the game. Nevertheless, in this example, the family decides to attend the game because of their already sunk investments. Thaler (1980) explains this effect using Kahneman and Tversky's (1979) prospect theory and the principle of mental accounting (Thaler 1985). According to his explanation, sunken investments set a mental account "in the red," which causes individuals to assess further losses in the same domain as less painful compared to a situation without any sunken investments. This can cause people to continue to expend resources on a task on which, otherwise, had they not already invested any sunk costs, they would not have spent anything. Previous research demonstrated this effect for monetary investments in several experimental and empirical settings.

As is well known from this literature, higher monetary sunk costs increase the likelihood of the occurrence of the sunk cost effect (e.g., Arkes and Blumer 1985, Camerer and Weber 1999, Staw and Hoang 1995). With regard to purely *behavioral investments*, there is an absence of evidence from the field and only limited disputable experimental evidence (Cunha and Caldieraro 2009, 2010; Navarro and Fantino 2009); in fact, other scholars fail to replicate these experimental results (Otto 2010) or argue that there is no sunk cost effect for behavioral investments, such as time (Soman 2001).

Our research adds to the prior studies on the sunk cost effect in two important ways. First, we analyze the sunk cost effect for behavioral investments in a

real market setting. By using real market data, we can rule out the two—from our point of view—most likely explanations for the conflicting experimental results on the sunk cost effect for behavioral investment: (1) Human behavior may be sensitive to a variety of factors that do not occur in the same way in a laboratory setting as in the real world (Levitt and List 2007). Thus, the conflicting results may be partly driven by differences between the lab situations and a real market situation. (2) Behavioral sunk costs encompass a variety of factors, which may not be fully replicated in an experimental situation. In particular, studies that concentrate on the sunk cost effect for time may underestimate the full extent of the sunk cost effect for behavioral investments by neglecting other contributors such as effort. Our second contribution to the sunk cost literature is not only to provide evidence for the existence of the sunk cost effect for behavioral investments but also to show how IT can serve as an effective tool for alleviating behavioral sunk costs. Thus, our results might help decision makers to reduce their overall sunk costs and thereby the likelihood of the occurrence of the sunk cost effect, which in turn increases the quality of their decisions.

2.2. Hypotheses

Following the literature (e.g., Cunha and Caldieraro 2009), we build on the well-accepted *effort-justification mechanism* (Aronson and Mills 1959, Axsom 1989) as an underlying mechanism for a sunk cost effect for behavioral sunk costs. In their seminal experiment, Aronson and Mills (1959) show that people who go through an unpleasant process to achieve a specific outcome tend to value it more highly than those who achieve the same outcome with less effort. This relationship is predicted by Festinger's (1957) theory of cognitive dissonance. No matter how attractive a specific outcome is, it is rarely entirely positive, and always has some undesired aspects. If a person invested a great deal of effort to achieve this outcome, it is dissonant with the cognition that the outcome has also some negative aspects. The person can reduce this dissonance by altering the existing cognitions in two ways. She can persuade herself that the way to achieve the target was not as negative as it seemed, or, alternatively, she can either overrate the positive or underrate the negative aspects of the outcome. The more effort was experienced on the way to achieving the outcome, the more difficult it is to alter the cognition already embarked upon. Thus, a person who has experienced an unpleasant and effortful process, *ceteris paribus*, would find the outcome more attractive than a person who was spared such a process. Investing behavioral resources such as time or effort without approaching a desired target is an example of such

an unpleasant process.² Accordingly, the perceived desirability of an outcome is an increasing function of the sunken behavioral resources invested in an attempt to achieve it. For instance, a person might evaluate her ownership of an item more positively after investing a substantial amount of time and effort searching for it, even though the time and effort do not affect the characteristics of the item and, thus, are sunk. Via this mechanism, sunk behavioral investments could lead to a greater tendency to continue an endeavor even in situations where a person would have stopped the endeavor, had she not made any sunken behavioral investment. This behavior exactly matches the definition of the sunk cost effect and thus leads to our first hypothesis.

HYPOTHESIS 1. *A higher behavioral investment increases the likelihood of the occurrence of the sunk cost effect.*

The delegation of decision making to prevent human decision biases was first proposed by Fischhoff (1982). He suggested that, as a final debiasing solution, faulty decision makers should be replaced by a superior instance. Applied to the sunk cost effect, a decision maker should therefore be replaced in two distinct decision situations: (1) at the time of the investment or (2) at the time of the decision whether or not to continue the endeavor. In this work, we focus on the replacement of the decision maker in the former decision situation and analyze its impact on any subsequent decisions in the latter.

In general, the delegation of decision making can protect decision makers from behavioral investments. As an example, Bapna (2003, p. 153) states that automated agents in an online auction setting “are an obvious technology that could reduce bidding costs” where these bidding costs are equal to the behavioral investments necessary to participate in an auction. Obviously, there is a significant difference in the amount of time and effort required, and thus in the behavioral investment, between personally participating in an auction and delegating the participation to an automated agent. In addition, delegating to IT during the bidding process might protect decision makers from further decision biases that also induce behavioral investments. For example, the so-called *quasi-endowment effect* identified in auctions induces behavioral investments for auction participants. Each time a participant places a bid, she is the highest bidder for a very short period of time at least. Even without a legal claim on the item,

the bidder might develop a feeling of ownership of the item during this period (Heyman et al. 2004) and lose it each time after another bidder places a higher bid. According to the general idea of loss aversion, losing an item several times is much more painful than not obtaining the item only once (Kahneman and Tversky 1979). By detaching the bidder from the bidding process, the delegation of decision making arguably mitigates these contributors of behavioral investments. Thus, if there is a sunk cost effect for behavioral investments (i.e., if our first hypothesis holds), delegating decision making to IT reduces the occurrence of the sunk cost effect by mitigating different contributors of behavioral investments. This leads us to our second hypothesis:

HYPOTHESIS 2. *By mitigating the effects of different contributors of behavioral investments, delegating decision making to IT protects decision makers from behavioral investments, and thereby reduces the likelihood of the occurrence of the sunk cost effect.*

Figure 1 shows a graphical representation of both of our hypotheses. The first hypothesis predicts a positive effect of behavioral investments on the occurrence of the sunk cost effect, whereas the second hypothesis predicts that delegating to IT has the effect of protecting decision makers from behavioral investments, and therefore reduces the likelihood the sunk cost effect will occur. In the following, we present the research setup for the empirical testing of our hypotheses and explain how we contextualize these hypotheses.

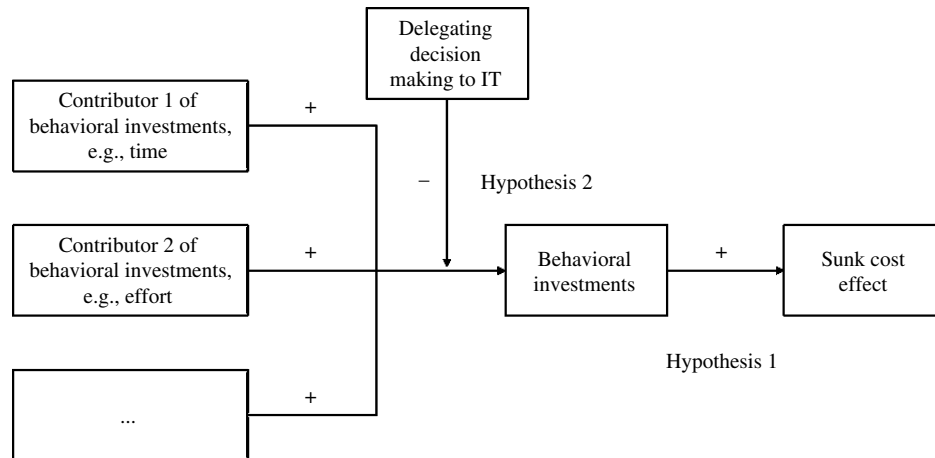
3. Research Setup

3.1. Description of the Auction Mechanism

Our study uses a data set provided by a large German website offering pay-per-bid auctions. Between August 28, 2009, and May 9, 2010, 6,995 pay-per-bid auctions were conducted on the website. Each auction starts at a price of zero, with a fixed end time displayed on a countdown clock. Auction participants are restricted to bidding a fixed bid increment (e.g., 1¢) above the current bid and must pay a nonrefundable fixed fee (e.g., 50¢) to place each bid. Each bid extends the duration of the auction by a given time increment (e.g., 10 seconds). For example, in an auction where the current bid is \$2.32 with 12 seconds on the auction countdown, an additional bid increases the current bid by 1¢ to \$2.33 and extends the auction countdown by 10 seconds. A participant wins the auction if her bid is not followed by another bid. To obtain the item, the winner pays the current bid in addition to the bidding fees already incurred. If the participant in our example is the last bidder, she wins the auctioned product for \$2.33. A direct-buy option allows participants who do not win the auction to directly buy the auctioned item for a buy-it-now price (known

² For example, Gill and Prowse (2012, p. 469) write, “Disappointment at doing worse than expected can be a powerful emotion. This emotion may be particularly intense when the disappointed agent exerted effort in competing for a prize, thus raising his expectation of winning.” This observation is a general characteristic of disappointment aversion (e.g., Bell 1985, Loomes and Sugden 1986).

Figure 1 Graphical Representation of the Hypotheses



prior to the commencement of the auction) net of their aggregated bidding fees paid for the bids placed in the auction. In our example, this would mean that a participant who had not won the auction but had placed 20 bids could directly buy the auctioned product for the posted buy-it-now price net of \$10, which is equal to 20 times the bidding fee of 50¢. Note that although there can only be one winner in each auction, there is no limit to the number of participants who can buy the product directly.

Bid increments on the focal auction website are €0.01 for 74%, €0.02 for 15%, €0.05 for 9%, and €0.10 for 2% of auctions. The bidding fee is constant at €0.50 for each auction, whereas the time increment varies between 10 and 20 seconds. In over 80% of auctions, a direct-buy option is offered to participants who fail to win it. As soon as an auction is completed, emails are sent to each unsuccessful auction participant reminding them of the opportunity to directly buy the product. The posted buy-it-now price is on average 4.8% above the price posted on Amazon.de at the respective end time of the auction. The average delivery time for each direct-buy item is posted in the respective auction description and is typically 10 days after payment is received.³

Auction participants have the opportunity to delegate their actual bidding to automated bidding agents. These agents are offered by the auction website at no cost and place a predefined number of bids automatically in a predefined price interval. To configure an automated bidding agent, auction participants must specify the number of bids and a price interval (lower and upper limits) in which these bids should be placed. After the auction price exceeds the lower bound of the price interval, the bidding agent starts bidding. The agent

places the bids at random points in time before the auction countdown expires. It stops bidding either (1) when the auction is won, (2) when the auction price exceeds the upper bound of the price interval, or (3) when the predetermined number of bids is depleted. The number of agents to be configured is not limited. Thus, for each auction, an auction participant may configure bidding agents with different numbers of bids and price intervals.

3.2. Contextualization of Hypotheses

In our context, participating in an auction without winning the item increases behavioral investments for four main reasons: (1) the necessary investment in time and effort to participate in the auction, (2) the quasi-endowment effect, (3) the highly competitive format of the auction, and (4) the series of small losses incurred during the bidding process. First, there is no certainty concerning the end time of an auction since the duration is extended with each bid placed. Therefore, bidders need to monitor auctions very closely and invest a substantial amount of time and effort in their participation. In the case of not winning the auction, the bidder made these investments without receiving anything in return. Second, as discussed in the hypothesis development section, the quasi-endowment effect further increases a bidder's behavioral investment in the auction. Third, the auction mechanism in pay-per-bid auctions typically leads to a very high degree of competition among auction participants (Byers et al. 2010). In contrast to an eBay-type auction, failing to win a pay-per-bid auction not only leads to missing out on the item but also to the loss of the bidding fees already incurred. This suggests that the comparably higher level of competition in pay-per-bid auctions constitutes an additional increase in the participant's behavioral investment (for a discussion of the effect of competition on bidding behavior, see Heyman et al. 2004). Fourth, bidders who submit their bids and do

³ The comparably long delivery time is caused by the business model of this website. Only items that are auctioned are kept in stock. Additional items for participants who exercise the direct-buy option are procured only after the orders are placed and paid for.

not win the item suffer a small monetary loss each time they place a bid, which further induces behavioral investment.

In the case of not winning an auction, all of these behavioral investments would be made in vain, that is, without having achieved the intended outcome, which, in turn, would increase the perceived unpleasantness of the bidding process (Gill and Prowse 2012). Accordingly, the perceived desirability of the auctioned item is an increasing function of the behavioral resources invested in the bidding process. Thus, a bidder may exercise the direct-buy option after investing a substantial amount of behavioral resources during the bidding process, even if the same person would not have exercised the direct-buy option if she had not invested any behavioral resources during the bidding process.

Using an automated bidding agent, however, mitigates all of the above-mentioned contributors of behavioral investments. First, because the bidding agent places the bids autonomously, participants who use an automated bidding agent do not need to monitor auctions, and therefore do not invest any time or effort in their participation. Second, for agent bidding, the quasi-endowment effect cannot play as important a role, because the agent bidder does not know at which point in time she is the highest bidder, and thus cannot develop a feeling of ownership of the auctioned item during the bidding process. Third, for agent bidding, the high degree of competition cannot cause behavioral investments. Because of their absence during the bidding process, participants who use an automated bidding agent are immune to personally experiencing competition during an auction. Fourth, delegating the bidding decisions to an automated bidding agent integrates the small losses incurred during the bidding process into one big loss. According to Kahneman and Tversky's (1979) prospect theory, individuals evaluate a series of small losses (e.g., 10 times \$1) more negatively than one bigger loss of the same amount (e.g., 1 time \$10). Naturally, manual bidders with such a value function should integrate a series of small losses into one big loss to minimize the negative value of a series of losses. However, Thaler and Johnson (1990) find that individuals are often cognitively unable to integrate a subsequent loss with an initial loss. For agent bidders, the automated bidding agent supports this integration of losses. Auction participants simply configure the bidding agent with a specified amount and are informed when the auction is won or the amount lost. They never experience a series of small losses. Thus, because bidders in manual participations cannot integrate their small losses, they evaluate the losses more negatively, and thereby experience higher behavioral investments than in participations where they place the same number of bids using an automated bidding agent.

In general, *ceteris paribus*, using an automated bidding agent substantially decreases the behavioral resources invested in the bidding process. Therefore, in participations where bidders employ an automated bidding agent and fail to win an auction, they perceive the bidding process as less unpleasant, and thus are less likely to exercise the direct-buy option due to their sunk behavioral investments.

3.3. Study Design

We can easily transfer Thaler's (1980) example of the sunk cost effect to pay-per-bid auctions with a direct-buy option: *An auction participant manually participates in a pay-per-bid auction to acquire an iPhone. After failing to win the auction, she decides to exercise the direct-buy option, but notes in passing that had she not invested any behavioral resources in the bidding process, she would not have bought the iPhone for the buy-it-now price net of the bidding fees spent.*

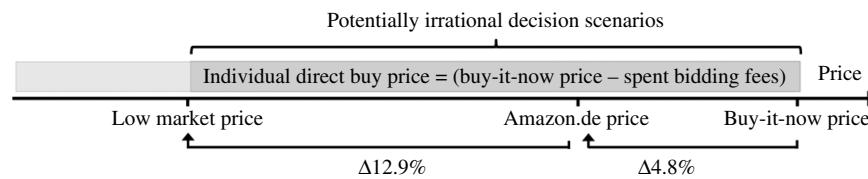
In an ideal empirical setting we would have data about each auction participant's private valuation of the auctioned product. This would allow us to directly observe if an auction participant executed the direct-buy option due to irrationality, or because her initial valuation of the product was higher than the buy-it-now price net of her spent bidding fees. (In the following, we call this price the *individual direct-buy price*.) For example, consider an auction participant who placed 80 bids worth \$40 in an auction with a buy-it-now price of \$800. After placing the bids, this person is offered to buy the product for the individual direct-buy price of \$760 (the buy-it-now price net of the spent bidding fees). If, at the beginning of the bidding process, this person values the product above \$760 and there is no other comparable (or better) retailer offering the product at a lower price, exercising the direct-buy option after having participated in the auction would be a rational decision.⁴ Conversely, if the valuation for the product was below \$760, it would be irrational to direct-buy the product. Unfortunately, it is not possible to directly observe this valuation in a nonexperimental setting.

However, in line with Malmendier and Lee (2011), we utilize publicly available price information⁵ from competing retailers to determine a very conservative threshold for direct-buy decision scenarios where direct buys are attributable to irrationality. If the publicly available price at a comparable (or better) retailer (which we call *low market price* in the following) is

⁴ Note that we neither analyze the decision to participate in the auction nor the determination of the bidding budget. We are only interested in the decision of whether to exercise the direct-buy option after participating in an auction.

⁵ We use the company's sourcing price for our main model and prices collected at Amazon.de for a robustness check to identify potentially irrational decision scenarios.

Figure 2 Identification of Potentially Irrational Decision Scenarios



lower than the individual direct-buy price (i.e., the buy-it-now price net of the spent bidding fees), a direct-buy decision by this participant can be considered irrational. In this case, the participant's valuation for the product can be either higher or lower than the low market price available at the competing website. If the valuation is lower than this price, it is always irrational to buy the product. If the valuation is higher than the low market price, a rational auction participant would always buy the auctioned product at a lower price from the competing website.⁶

We were able to collect prices posted on Amazon.de for a total of 3,021 auctions.⁷ These prices are on average 4.8% lower than the buy-it-now prices on the auction website. Given the widespread price dispersion online (Clemons et al. 2002) and the trend of higher prices being charged by reputable retailers (Smith and Brynjolfsson 2001), the posted buy-it-now price is usually much higher than the lowest price available online. Smith and Brynjolfsson (2001) find that buyers are willing to pay a premium of approximately 10% to buy from Amazon.com instead of a different, less reputable retailer with a similar offer. In addition, prior research suggests that shipment conditions and delivery times play an important role in determining a consumer's willingness to pay (Pan et al. 2002). Considering both the retailer's reputation and the delivery times, Smith and Brynjolfsson (2001) state that the majority of customers in their sample chose an offer that was up to 20.4% higher than the cheapest offer.

Given the relatively longer delivery times and the low reputation, our focal site is naturally unlikely to be the first choice for an auction participant when they consider buying a product at their individual direct-buy price.⁸ Rather, in all likelihood, participants are willing to pay a substantial premium to buy from Amazon

(Smith and Brynjolfsson 2001), and compare their individual direct-buy prices with low prices from other retailers that are more comparable to the focal site in terms of reputation and delivery times. Fortunately, the sourcing prices of the directly bought items, which the management of the website made available to us, give us a good estimate for these low prices. Because the company did not keep items in stock, but ordered the sold items from different online retailers immediately after receiving the payment, the sourcing prices are—at the least—representative of low market prices available online. In addition, the company restricted their sourcing to a few key online retailers, and since they ordered only limited quantities, there was practically no room for bulk-buy discounts. Consistent with the findings from prior research, the sourcing prices observed are on average 12.9% lower than respective prices posted on Amazon.de. More importantly, as the focal company sourced products only from a few key retailers that were easily accessible to the general public, auction participants could directly purchase the products for the sourcing price, and even at lower prices. Thus, the sourcing price provides an upper bound for the low market price available for each directly bought item. Consequently, we identify a decision scenario as irrational if a participant's individual direct-buy price is higher than the company's sourcing price of the respective product. Figure 2 illustrates this approach.

We note that this approach is quite conservative because there could be participants whose valuation for the product is significantly lower than the low market price cutoff in Figure 2. If the individual direct-buy price for such a participant falls in between her valuation and the low market price, it is irrational for her to exercise the direct-buy option. Since we do not know the exact valuation of the auction participants, we do not arbitrarily assume the cutoff point. Rather, we use the upper bound of the lowest price for each product as the cutoff point. Hence, this approach is likely to exclude potential direct-buy decisions that are attributable to the sunk cost effect from our sample. Not surprisingly, all the results presented in the following sections are robust to including these observations by sliding the low market price cutoff to the left.

⁶ This is consistent with the classical economic premise that consumers are focused on maximizing their surplus. Accordingly, a consumer should not pay more than the market price, irrespective of his private valuation. Many bloggers and news articles suggest that most participants of these types of auctions are deal seekers who tend to be price sensitive (e.g., Diaz 2009). This implies that this type of participant is more inclined to use a price comparison site to find a lower price.

⁷ We collect prices only for products that were in stock at the respective end time of an auction.

⁸ From the launch day of the website until the end of our observation period, the website sold only 6,337 units, which left no room for building up any reputation. Additionally, the pay-per-bid auction

format was met with controversy in online discussions and in the media. For example, a famous blogger called the business model "as close to pure, distilled evil in a business plan as I've ever seen" (Atwood 2008). These discussions might also have a negative impact on the company's reputation.

3.4. Data Set

Our data set contains customer-level bidding and transaction data for all auctions conducted between August 28, 2009, and May 9, 2010. For each auction participation, we have information about the actual bidding behavior of each participant; the bidding method used (agent or manual bidding); the number of bidding agents; the auctioned product; whether or not the auction included a direct-buy option and, if it did, whether, when, and by whom this option was exercised; and the buy-it-now price. Regarding participants, we know the date of their registration, the number of bought bids, as well as basic demographic information such as gender and age. Our data set encompasses 483,414 auction participations involving 87,038 distinct participants, who placed an overall 6,463,642 bids in 6,995 auctions for 408 different products. Of these auctions, 5,763 included an option to directly buy the product. This option was exercised 6,337 times by 2,585 distinct participants.

3.5. Main Variables

Our research design allows us to analyze the effects of behavioral investments on irrational decisions, as well as the moderating effect of bid agent usage on the different contributors of behavioral investment. In §3.2, we identified four major contributors of these investments: (1) the time and effort required to participate in the auction, (2) the quasi-endowment effect, (3) the very high degree of competition in this auction format, and (4) the failure to integrate a series of losses. Naturally, all of these contributors of behavioral investments are closely related to the number of bids placed. Therefore, we use the variable *Number_of_Bids*, which is equal to the total number of bids placed by the auction participant in a particular auction, to capture a participant's behavioral investments. *Number_of_Bids* also acts as a control variable for a participant's monetary investment. Because participants have to pay a fixed bidding fee for each bid placed, this variable is a reliable measure for a participant's monetary investment. Thus, *Number_of_Bids* is a measure for both monetary and behavioral investments, where the monetary investment captured by this variable is not influenced by either manual or agent bidding.

To account for differences in behavioral investments for manual and agent bidding, we include a variable named *Bid_Agent_Dummy*, as well as the interaction of *Number_of_Bids* and *Bid_Agent_Dummy* in our model. *Bid_Agent_Dummy* equals one if a bidder placed more than 75% of the bids in a specific auction participation using an automated bidding agent. Holding constant the number of bids placed (and thereby the monetary investment), any difference between the effects of *Number_of_Bids* for manual and agent bidding is attributable to the difference caused by the participant's

behavioral investments. Therefore, a significantly larger effect of *Number_of_Bids* for manual participations, i.e., a significantly negative interaction term between *Number_of_Bids* and *Bid_Agent_Dummy*, would provide support for both of our hypotheses. First, a significantly negative interaction term, and therefore a significantly lower effect of *Number_of_Bids* for agent bidding, would provide evidence for the sunk cost effect for behavioral investments. Second, such an effect would show that delegating to IT significantly decreases behavioral investments because the likelihood of the occurrence of the sunk cost effect is significantly smaller for auction participations where the bidder delegated the bidding decisions to an automated bidding agent.

Nevertheless, setting up automated bidding agents may also cause some behavioral investment. Agent usage requires a participant to decide on the number of bids as well as on the price interval in which these bids should be placed. The variable *Bid_Agent_Dummy* partially controls for this effect. However, depending on whether the bidder configures only one as opposed to several bidding agents, the level of the behavioral investment may differ significantly. We therefore include the variable *Number_of_Bid_Agents*, which is equal to the number of bidding agents used by a participant in a specific auction, as a control variable in our econometric model.

To account for potential time-varying heterogeneity across auction participations, we include the variable *Number_of_Participations* as a historical experience measure in our model. This variable is defined as the number of participations by a specific participant in different auctions since the day of registration. As the economics and marketing literatures suggest, people evaluate potential savings not only in absolute value but also by assessing their savings in relation to the absolute price of a product (e.g., Grewal and Marmorstein 1994). For example, a \$5 discount for a product with a price tag of \$10 is valued higher than the same discount for a product worth \$1,000. To control for this issue, we include a variable named *Buy-it-Now_Price* in our model. It is defined as the posted buy-it-now price of each product and is measured in euros. Finally, we control for the end time of the auction. For that purpose, we divide the day into two 12 hour intervals, starting at midnight, and include one dummy variable (*Midnight-Noon_Dummy*).

4. Empirical Analysis

4.1. Basic Model

The occurrence of the sunk cost effect is represented by a binary variable equaling one if the direct-buy option is exercised in an potentially irrational decision scenario. Accordingly, we use a logistic panel regression model to examine the impact of the bidding agent usage on the likelihood of the occurrence of the sunk cost

effect. The panel structure of our data set allows us to control for the individual time-constant heterogeneity of auction participants (Hsiao 2003). For example, some auction participants may be more tech savvy or have a higher general ability than other participants. To utilize this advantage, we can estimate both fixed and random effects models (for a general discussion of when to use fixed or random effects models, see Hsiao 2003). An important advantage of the fixed effects model is that it allows for the individual specific effects to be correlated with explanatory variables. For the random effects model, such correlation is not allowed (Hsiao 2003). However, the flip side of the fixed effects model is that estimates are solely based on within-person variation and completely ignore the between-person variations. This often yields standard errors that are considerably higher than those produced by methods that consider both within- and between-person variations (Allison 2005). For our data set, we expect the individual specific effects to be correlated with the explanatory variables. For example, a person with a higher (unobservable) risk preference may spend more bids while participating in a pay-per-bid auction. The significant test statistic (89.39; $p < 0.0001$) in favor of the fixed effects model for the Hausman (1978) specification test supports our choice of model. Nevertheless, the results remain qualitatively unchanged if we estimate a random effects model where no such restriction is imposed.

Accordingly, we estimate a fixed effects logistic regression model to test for a direct effect of behavioral sunk costs on irrational decisions to directly buy a product and, more importantly, for a potential effect of IT usage on this relationship. We include in our model the variables *Number_of_Bids* and *Bid_Agent_Dummy* as well as their interaction. We further add the control variables presented in the preceding subsection. Thus, we consider the following model in latent variable form (Wooldridge 2010):

$$Y_{ij}^* = \alpha + \beta_1 X_{1ij} + \beta_2 X_{2ij} + \beta_3 X_{1ij} \cdot X_{2ij} + \beta D_i + \mathbf{s}Z_{ij} + \varepsilon_{ij}, \quad (1)$$

$$Y_{ij} = 1 [Y_{ij}^* > 0],$$

where Y_{ij} is a dummy variable equaling one if a participant i exercises the direct-buy option in auction j , X_{1ij} denotes the number of bids a participant i placed in auction j , X_{2ij} is a dummy variable indicating if a participant i uses an automated bidding agent in auction j , D_i is a set of dummy variables indicating individual fixed effects, Z_{ij} is a vector of control variables, and ε_{ij} is the random error term.

Note that because of its focus on only within-person variation, this model specification controls for all the time-invariant factors, including any differences that are inherent in participants, e.g., propensity for risk taking, basic ability to use bidding agents, and intellectual ability. More importantly, the individual fixed effects,

along with the time-variant and participant-specific variable *Number_of_Participations*, collectively address any concerns regarding the self-selection of participants who use an automated bidding agent. Thus, the fixed effects model allows us to address endogeneity concerns in a meaningful and robust manner (Allison 2005).

4.2. Sample

In deriving our sample, we drop all the observations that represent potentially rational direct-buy decisions. This specifically concerns all the observations where the individual buy-it-now price is below the sourcing price of our analyzed company. Thus, we keep only those observations where the buy-it-now price net of the spent bidding fees is above the low market price available online (i.e., decision situations that are marked as “Potentially irrational decision scenarios” in Figure 2). To isolate the impact of IT usage on the sunk cost effect, we restrict the remaining data to instances where auction participants in a specific auction placed more than 75% of their bids either with or without an automated bidding agent.⁹ We further drop all observations where the respective auction did not include a direct-buy option, or where the respective participant won the auction. Because the conditional fixed effects model requires variation in the independent variable (Wooldridge 2010), we focus on individuals who participated at least twice and executed the direct-buy option at least once, but not in each of their participations. This leaves us with a sample of 230 distinct individuals who faced a total of 3,153 potentially irrational decision scenarios; thus we have, on average, 14 participations for each individual. The direct-buy option was executed 240 times. In other words, our sample is an unbalanced panel data set consisting of 230 individuals and 3,153 observations. Table 1 lists summary statistics for this sample, sorted by bidding method.

4.3. Main Results

Column (1) of Table 2 presents the estimates of the fixed effects model. In line with the conclusions of the literature pertaining to monetary investments, we find a very strong and highly significant positive relationship between the number of bids placed and the likelihood to exercise the direct-buy option for manual

⁹ We do not limit our sample to participants who placed all of their bids with only one of the bidding technologies because IT usage should also reduce the behavioral investments of auction participants who submitted a large fraction of their bids with an automated bidding agent. Our main results are not affected by the decision on the threshold where we identify a bidder as an agent bidder. In particular, we estimated our models for thresholds of, respectively, 50%, 75%, 90%, and 100% and always obtained qualitatively the same results. The results of these robustness checks are available from the authors upon request.

Table 1 Descriptive Statistics

	Manual bidding, $N = 2,604$					Agent bidding, $N = 549$				
	Mean	Std. dev.	Min	Median	Max	Mean	Std. dev.	Min	Median	Max
<i>Direct_Buy</i>	0.06	0.24	0	0	1	0.14	0.34	0	0	1
<i>Number_of_Bids</i>	9.18	25.37	1	2	476	35.77	48.14	1	20	501
<i>Number_of_Participations</i>	37.87	65.26	0	11	444	78.53	114.7	7	29	437
<i>Buy-it-Now_Price</i> (in €)	358	318	15	237	1,337	395	325	19	259	1,337
<i>Midnight-Noon_Dummy</i>	0.27	0.44	0	0	1	0.34	0.47	0	0	1
<i>Number_of_Bid_Agents</i>	0.09	0.39	0	0	6	2.66	2.58	1	2	19
<i>Log_Time_Investment</i>	8.13	6.69	0	11.10	17.88	10.20	5.91	0	12.73	18.07
<i>Relative_Investment</i>	2.15	4.34	0.04	0.58	43.12	6.24	6.96	0.06	3.79	50

Table 2 Main Results

Variable	Main model (1)	Time investment (2)	Relative investment (3)	105% sourcing (4)	110% sourcing (5)	Amazon price (6)	PSM (7)
<i>Number_of_Bids</i>	0.105*** (0.009)	0.094*** (0.010)	0.018** (0.008)	0.105*** (0.011)	0.107*** (0.015)	0.187*** (0.054)	0.076*** (0.016)
<i>Bid_Agent_Dummy</i>	−1.024** (0.493)	−0.549 (0.805)	−2.033** (0.798)	−0.580 (0.555)	−0.634 (0.652)	−3.061* (1.719)	−1.020** (0.471)
<i>Number_of_Bids</i> × <i>Bid_Agent_Dummy</i>	−0.062*** (0.008)	−0.053*** (0.009)	−0.019* (0.010)	−0.067*** (0.010)	−0.076*** (0.014)	−0.102** (0.044)	−0.036** (0.016)
<i>Number_of_Participations</i>	0.009 (0.007)	0.007 (0.007)	0.009 (0.010)	0.034** (0.014)	0.026 (0.016)	−0.006 (0.036)	−0.018*** (0.004)
<i>Buy-it-Now_Price</i>	−0.010*** (0.001)	−0.010*** (0.001)		−0.008*** (0.001)	−0.007*** (0.001)	−0.013** (0.006)	−0.009*** (0.002)
<i>Midnight-Noon_Dummy</i>	0.339 (0.282)	0.363 (0.288)	0.072 (0.332)	0.097 (0.315)	0.343 (0.350)	−0.583 (1.265)	0.390 (0.383)
<i>Number_of_Bid_Agents</i>	0.828*** (0.109)	0.797*** (0.112)	0.800*** (0.128)	0.719*** (0.127)	0.728*** (0.154)	1.458** (0.658)	0.755*** (0.110)
<i>Log_Time_Investment</i>		0.077** (0.032)					
<i>Log_Time_Investment</i> × <i>Bid_Agent_Dummy</i>		−0.047 (0.068)					
<i>Relative_Investment</i>			0.443*** (0.054)				
<i>Relative_Investment</i> × <i>Bid_Agent_Dummy</i>			−0.134** (0.065)				
<i>Intercept</i>							−1.958*** (0.403)
Log likelihood	−149.82	−146.51	−103.21	−117.65	−92.25	−17.90	−139.78
Number of observations	3,153	3,153	3,153	1,770	1,186	236	1,058
Number of participants	230	230	230	165	119	50	177

Notes. Standard errors are in parentheses. PSM, propensity score matching.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

as well as for agent participations.¹⁰ More important for our analysis is the coefficient on the interaction

¹⁰ To calculate the direct effect of the *Number_of_Bids* variable for agent users, we need to combine the coefficients of *Number_of_Bids* and the interaction term, which gives us a combined coefficient of 0.043. The standard error for the coefficient is equal to $\sqrt{\text{var}(\hat{\beta}_1) + \text{var}(\hat{\beta}_3) + 2\text{cov}(\hat{\beta}_1, \hat{\beta}_3)}$, where $(\hat{\beta}_1)$ is the coefficient on *Number_of_Bids*, and $\hat{\beta}_3$ is the coefficient on the interaction of *Bid_Agent_Dummy* and *Number_of_Bids* (s.e. = $\sqrt{0.009^2 + 0.008^2 + 2(-0.00006) = 0.005}$) (Brambor et al. 2006). Thus, *Number_of_Bids* is also highly significant for agent users. Nevertheless, the impact of monetary investments in this context should be interpreted with some caution because the individual direct-buy price decreases with the number of bids.

term between *Number_of_Bids* and *Bid_Agent_Dummy*. Consistent with Hypotheses 1 and 2, the coefficient for the interaction of these variables is negative and highly significant. Thus, for participations where bidders delegate their bidding to an automated agent, the effect of *Number_of_Bids* on the likelihood to exercise the direct-buy option is significantly lower than for manual participations of the same bidder. In other words, given the same number of bids placed, it is significantly less likely that a bidder executes the direct-buy option in a potentially irrational decision scenario if she uses an automated bidding agent. This result provides a strong indication that there is a sunk cost effect for behavioral

investments and that delegating to IT can reduce these investments. In the following, we discuss the economic significance of these results.

4.4. Economic Significance of Main Results

Because we estimate a logistic regression model, the coefficients cannot be interpreted as the change in the mean of Y_{ij} for a one unit increase in the respective predictor variable, with all other predictors remaining constant.¹¹ Rather, they can be interpreted as the natural logarithm of a multiplying factor by which the predicted odds of $Y_{ij} = 1$ change, given a one unit increase in the predictor variable, holding all other predictor variables constant.¹² Therefore, we first have to calculate the odds ratio, which is equal to the exponent of the coefficient of the respective variable.

Column (1) of Table 2 shows that the coefficient associated with *Number_of_Bids* is 0.105. Thus, the odds ratio for this variable is equal to $\exp(0.105) = 1.111$. Because *Number_of_Bids* is part of the interaction term (*Number_of_Bids* \times *Bid_Agent_Dummy*), the coefficient does not represent a main effect, but represents a conditional effect instead, i.e., the effect of a one unit increase of *Number_of_Bids* when the moderator variable is zero. Thus, 1.111 is the multiplying factor by which the odds of directly buying the product changes with each additionally placed bid for participations where a bidder does not use an automated bidding agent. Put differently, the odds for buying the product directly increase by about 11% for each additional bid placed manually.

Next, we want to assess the effect of *Number_of_Bids* on the odds of buying the product directly for participations where a bidder uses an automated bidding agent. Here, we need to take the exponent of the sum of the coefficients of *Number_of_Bids* and the interaction term *Number_of_Bids* \times *Bid_Agent_Dummy*. The resulting odds ratio is 1.048, implying that a one unit increase in *Number_of_Bids* increases the odds of directly buying the product by 5%. This is less than 50% of the increase for participations where a bidder does not use an automated bidding agent. For example, consider a participation where the bidder placed 67 bids.¹³ If this participant had placed her bids manually, the odds of buying the product directly are approximately 1,130 times higher than if she had not placed a bid. Conversely, if this participant placed her bids via an

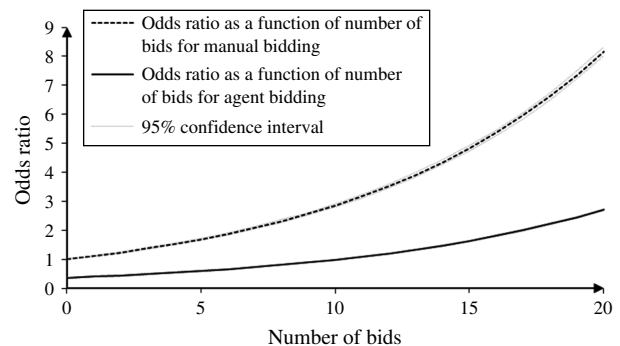
automated bidding agent, her odds are only 23 times higher compared with not having placed any bid. This result strongly supports Hypotheses 1 and 2.

In addition to the indirect effect, there is also a direct effect of bid agent usage on the likelihood of the occurrence of the sunk cost effect. To assess this effect, we first need to take the exponent of the coefficient of *Bid_Agent_Dummy*. The resulting odds ratio is 0.359, which implies that the base odds of buying the product directly must be multiplied by 0.359 if a participant uses an automated bidding agent instead of bidding manually. In this regard, we also need to consider the effect of *Number_of_Bid_Agents*. The exponent of the coefficient on *Number_of_Bid_Agents* is 2.289. Thus, we need to multiply the base odds by 2.289 for each additionally configured bidding agent. In other words, each additionally configured bidding agent increases the odds of the occurrence of the sunk cost effect.

To analyze the total effect of bidding agent usage on the likelihood to exercise the direct-buy option, we need to combine the effects of *Number_of_Bids*, *Bid_Agent_Dummy*, and *Number_of_Bid_Agents* and compare this combined effect with the effect of *Number_of_Bids* for participations where a bidder places bids manually. Figure 3 shows the resulting odds ratios for participations with 0.07 automated bidding agents per placed bid—which is the average number of configured agents per bid for agent participations—and for manual participations. As can be seen from this figure, the odds ratio is an increasing function of the number of placed bids for manual and agent bidding. When a bidder places bids manually, her odds ratio will always be higher compared to situations where bids are placed with an automated bidding agent. This figure illustrates the evidence in support of both of our hypotheses: A sunk cost effect exists for behavioral investment, and IT can reduce behavioral investments and thereby decrease the likelihood of the occurrence of the sunk cost effect.

Our research design allows us to quantify the difference between the behavioral investments of agent and manual participations using a monetary equivalent. For

Figure 3 Odds Ratio as a Function of *Number_of_Bids*

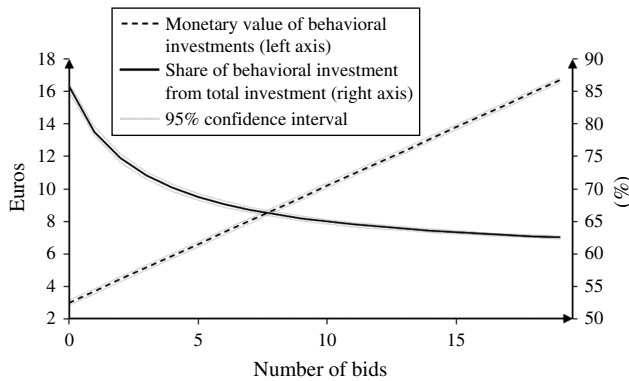


¹¹ This applies especially to interaction effects in logit (and other nonlinear) models. In such models, the magnitude of the interaction effect does not equal the marginal effect of the interaction term and can even be of opposite sign (Ai and Norton 2003). In fixed effects logistic regression models, such interaction effects should be interpreted using odds ratios (Karaca-Mandic et al. 2012).

¹² The odds are defined as $Odds = P(Y_{ij} = 1) / (1 - P(Y_{ij} = 1))$.

¹³ This is equal to the average number of bids placed by participants who exercised the direct-buy option.

Figure 4 Monetary Valuation of Behavioral Investments



each number of manually placed bids, we can easily find the respective number of bids a bidder needs to place with an automated bidding agent to obtain a similar odds ratio. The difference between these numbers, multiplied by the bidding fee, is equal to the monetary value of the difference between the behavioral investment of manual and agent bidding. Figure 4 shows this difference (dashed line) and the ratio of this difference and a participant's total investment (solid line) as a function of the number of placed bids. Figure 4 shows that in manual bidding situations, each additionally placed bid increases the bidder's behavioral investment by an amount equal to a monetary investment of €0.72. Thus, behavioral investments account for approximately 60% of a manual bidder's total investment, i.e., monetary and behavioral investments, in a pay-per-bid auction.

5. Alternative Operationalization of Behavioral Investments

So far we have tested the combination of both of our hypotheses based on different effects of the *Number_of_Bids* variable for manual and agent bidding. To gain deeper insights into our results, we utilized separate measures for monetary and behavioral investments. This allows us to individually test both of our hypotheses. A significant positive effect for a measure of behavioral investments on the likelihood of the occurrence of the sunk cost effect would provide support for the first hypothesis, whereas an insignificant effect of these investments for agent bidding would provide support for the second hypothesis.

First, we use the variable *Log_Time_Investment* as a proxy for a participant's behavioral investments and keep the variable *Number_of_Bids* as a measure for the monetary investment. *Log_Time_Investment* is defined as the natural logarithm of the time difference¹⁴ between

a participant's first and last bids in an auction and captures the time invested in participation. If we assume that our results are mainly driven by the difference in a bidder's time investments for agent and manual participations, we would expect this variable to have a significantly positive effect for auction participations where the bidder places her bids manually, but to be insignificant for agent participations of the same bidder. To capture this difference, we include the interaction of *Log_Time_Investment* and *Bid_Agent_Dummy* in our model.

Column (2) of Table 2 shows the regression results for this alternative model specification. Confirming our expectation, we find a significant positive coefficient for *Log_Time_Investment*. The estimated coefficient for this variable is 0.077 (s.e. = 0.032). Again, note that because of the interaction between *Log_Time_Investment* and *Bid_Agent_Dummy*, this is the effect of *Log_Time_Investment* conditional on *Bid_Agent_Dummy* being equal to zero. For manual bidding, a higher time investment increases the likelihood of the occurrence of the sunk cost effect. In considering the effect of *Log_Time_Investment* for agent bidding, we need to combine the direct effect and the interaction effect to compute the total effect of *Log_Time_Investment* on the occurrence of the sunk cost effect. Combining these two effects results in an estimated insignificant coefficient of 0.030 (s.e. = 0.060)¹⁵ on *Log_Time_Investment* for agent bidding. Confirming our first hypothesis, investing more time in an auction has a significant positive effect for manual participations. Confirming our second hypothesis, there is no effect of the invested time during the bidding process in agent participations of the same bidder.

Even in this extended model, the coefficients of *Number_of_Bids* for manual bidding (0.094, s.e. = 0.0099) and agent bidding (0.094 – 0.053 = 0.041, s.e. = 0.006) differ significantly. Thus, *Log_Time_Investment* captures only one part of a participant's behavioral investments, whereas the other is captured in the *Number_of_Bids* variable. This result provides a strong indication for other contributors of behavioral investments, i.e., the quasi-endowment effect, the series of small losses, and the high degree of competition in pay-per-bid auctions, which are not linked to the time invested in the bidding process playing an important role in our context.

To account for the importance of non-time-related contributors of behavioral investments, we keep *Number_of_Bids* as a measure for behavioral investments and use a participant's relative monetary investment in an auction as a measure for monetary investments. In an experimental study, Garland and

¹⁴ We increase the time difference by 1 second so that *Log_Time_Investment* is also defined for participants who place only 1 bid.

¹⁵ The coefficient can be calculated by summing up the coefficients on *Log_Time_Investment* and the interaction between *Log_Time_Investment* and *Bid_Agent_Dummy* (0.077 – 0.047 = 0.030). The standard error of the coefficient is equal to $\sqrt{0.032^2 + 0.068^2 + 2(-0.001)} = 0.060$.

Newport (1991) find that for monetary investments only the relative rather than the absolute magnitude of sunk costs had a significant impact on the occurrence of the sunk cost effect. After controlling for a participant's relative monetary investment, they do not find any significant effect for the absolute sunk costs. Based on their result, we would expect *Number_of_Bids* to capture behavioral investments only if we were to include the variable *Relative_Investment*, defined as the ratio of the invested bidding fees and the buy-it-now price, to control for a participant's relative monetary investment.¹⁶

Column (3) of Table 2 presents the estimates of this alternative operationalization of monetary investments. For manual auction participations, the coefficient on *Number_of_Bids* is positive and highly significant. Confirming our first hypothesis, behavioral investments exert a significant positive effect on the occurrence of the sunk cost effect. For agent participations, the effect of *Number_of_Bids* is approximately zero and insignificant. Thus, for participations where a bidder delegated her decision making to IT—holding the relative monetary investment constant—a higher number of bids placed does *not* affect the likelihood of the occurrence of the sunk cost effect. Again, this result provides support for both of our hypotheses. The significant positive coefficient for the *Number_of_Bids* variable for manual bidding shows that there is a sunk cost effect for behavioral investments. The insignificant effect of this variable for agent bidding strongly supports our second hypothesis. Delegating the bidding process to IT mitigates the impact of different contributors of behavioral investments, and thereby reduces the occurrence of the sunk cost effect.

6. Robustness Checks

Although we find support for both of our hypotheses for all these operationalizations of behavioral investments, we have examined a number of competing explanations for the effects observed. In the following, we demonstrate that our results withstand a wide range of robustness checks.

6.1. Quality of External Price

One could argue that this company's sourcing price does not provide a perfect estimate for the reference price of auction participants. Even though the website we analyze has not yet built up a sufficient reputation and only offers comparatively long delivery times, there may be participants who nevertheless, and despite negligible price differences, prefer to transact with the

focal site, or there may be participants who do not compare their individual direct-buy price with a low price available online, but with a price from a more reputable retailer. If auction participants are only aware of prices higher than the company's sourcing price, or they are willing to pay a premium to buy at the analyzed website, or they experience nonnegligible search costs, we would risk misidentifying some rational direct-buy decisions as irrational. For example, consider an auction participant who invested \$40 in an auction with a buy-it-now price of \$800. After placing her bids, this person could buy the product for \$760 (the buy-it-now price net of the spent bidding fees) from our website. In addition, this person incurs nonnegligible search costs of, say, \$5. In this case, it would be a rational decision for this person to purchase from this website, even if there were other—comparable or better—retailers offering the same product for \$756. Furthermore, there may also be some costs associated with switching from this auction website to a retailer offering the low market price. If these switching costs are higher than the difference between the low market price and the individual direct-buy price, the respective direct-buy decisions cannot be attributed to irrationality.

We are able to address these concerns by increasing our estimate for a low price available online. Accordingly, we reestimate our main model on data sets where we raise the threshold stepwise for decisions that we identify as irrational. In the first step, we consider only participants faced with decision scenarios where their individual direct-buy price was above 105% of the company's sourcing price. Subsequently, we increase this threshold value to 110%. As a very strict robustness check, we compare a participant's individual direct-buy price with the price posted on Amazon.de at the end time of the auction. For this robustness check, we identify as irrational only those decision scenarios where the individual direct-buy price was higher than the respective price posted on Amazon.de. This is a very strict robustness check because it assumes that participants have no preference either to buy from a reputable retailer or to benefit from a shorter delivery time. These assumptions are in direct contradiction with the empirical results of previous research (e.g., Smith and Brynjolfsson 2001). The results of these robustness checks are presented in columns (4)–(6) of Table 2. Reassuringly, our main coefficients remain qualitatively unchanged. These results reaffirm our key findings and show that the results from our main model are not biased due to an imprecise estimate of a low price available online.

6.2. Self-Selection Arising from Bidding Agent Usage

As mentioned before, the fixed effects model can be quite effective in addressing potential self-selection

¹⁶ Note that *Relative_Investment* additionally takes over the function of *Buy-it-Now_Price*. Therefore, we exclude *Buy-it-Now_Price* from this model specification.

Table 3 Matching Variables Before and After Propensity Score Matching

	Unmatched				Matched			
	Treated	Control	t^a	$p > t $	Treated	Control	t^a	$p > t $
<i>Number_of_Participations</i>	78.53	37.87	11.36	0.000	69.66	70.21	−0.09	0.929
<i>Number_of_Wins</i>	3.19	1.53	9.74	0.000	3.02	3.10	−0.27	0.787
<i>Number_of_Direct_Buys</i>	2.57	1.40	9.25	0.000	2.39	2.46	−0.30	0.762
<i>Days_Since_Last_Participation</i>	2.86	1.98	2.37	0.018	2.92	3.08	−0.26	0.798
<i>Number_of_Bids_Last_Auction</i>	44.29	33.99	1.78	0.075	39.45	44.46	−0.63	0.532
<i>Gender</i>	0.26	0.27	−0.46	0.646	0.27	0.24	1.20	0.230
<i>Age</i>	38.06	36.59	3.00	0.003	37.81	38.08	−0.30	0.761
<i>Former_Experience_Bid_Agent_Dummy</i>	0.81	0.57	10.66	0.000	0.80	0.79	0.38	0.704

^a t -value obtained from a t -test for equality of means in the treated group and the control group.

due to time-invariant unobserved heterogeneity; still, we can further verify the robustness of our results by utilizing the propensity score matching method suggested by Rosenbaum and Rubin (1983).¹⁷ This method is commonly used to control for self-selection effects due to individual specific time-variant and time-invariant unobserved heterogeneity. In particular, we can address concerns that bidders learn during their participations and, therefore, are more rational in later participations. The basic idea of propensity score matching is to find a sample of the control group (i.e., participations where a bidder does not use an automated bidding agent) that is similar to the treatment group (i.e., participations where a bidder uses an automated bidding agent) in all relevant pretreatment characteristics. For example, in this approach, the impact of familiarity or experience with the auction platform on bidding agent usage and the sunk cost effect—controlled for in the fixed effects model through the variable *Number_of_Participations*—is considered in a different way. When this is applied, the difference in outcomes for both groups can be attributed solely to the treatment rather than to self-selection effects.

We use the variable *Bid_Agent_Dummy* to indicate whether an observation belongs to the treatment or to the control group. For each individual in the treatment group, we try to find a *statistical twin* who does not differ in any of the relevant pretreatment characteristics. Because the dimensionality of observable characteristics is high, it is not an easy task to decide which dimensions to match or which weighting scheme to adopt. In such cases, propensity score matching is a useful method because it provides a natural weighting scheme that yields unbiased estimates of the treatment impact (Dehejia and Wahba 2002). To calculate the propensity score for each observation, we estimate a logit model with *Bid_Agent_Dummy* as the dependent variable and the following covariates: variables measuring the participants' experience with the auction

website (*Number_of_Participations*, *Number_of_Wins*, *Number_of_Direct_Buys*, *Days_Since_Last_Participation*), their behavior in the last auction (*Number_of_Bids_Last_Auction*), their *Gender* and *Age*, and their affinity with technology (*Former_Experience_Bid_Agent*). Subsequently, we use caliper matching without replacement to match each treated observation to its nearest untreated neighbor based on the propensity score.

We find that before matching, the control group differs significantly from the treatment group in all pretreatment characteristics. However, after matching, the difference between the matched control group and the treatment group is insignificant on all these dimensions. Table 3 provides an overview of the matching variables before and after matching. Because the treatment and control groups do not differ significantly in any of the pretreatment characteristics, we can use both within- and between-person variation to estimate our coefficients. Accordingly, we estimate a logistic regression model with standard errors clustered on the individual level for this matched subsample. The results presented in column (7) of Table 2 are very similar to those in column (1). As in our main analysis, the coefficient for the variable *Number_of_Bids* is positive and highly significant, whereas the coefficient for the interaction term of *Number_of_Bids* and *Bid_Agent_Dummy* is negative and significant. This further strengthens our confidence in our results not being biased through the self-selection of participants using an automated bidding agent.

6.3. Nonparametric Matching Model

An additional check for ruling out alternative explanations, and to further assess the robustness of our main results, is to follow Pope and Schweitzer (2011) by conducting nonparametric analyses. This allows us to address concerns about time-varying unobserved factors, e.g., product- or auction-specific characteristics. Although we lose some statistical power with this approach, it enables us to compare agent and manual bidding in a novel way. In addition, because nonparametric tests are not based on a statistical model,

¹⁷ We used the Stata PSMATCH2 module by Leuven and Sianesi (2009) to implement propensity score matching. An extensive discussion of the method can be found in Guo and Fraser (2010).

Table 4 Nonparametric Matched Sample Analysis

	Maximum difference in the number of bids placed for the same product between matched potentially irrational decision scenarios with and without bidding agent <i>across auctions</i>			Maximum difference in the number of bids placed for the same product <i>in the same auction</i> between matched potentially irrational decision scenarios with and without bidding agent		
	Exact match (1)	≤ 5% (2)	≤ 10% (3)	Exact match (4)	≤ 5% (5)	≤ 10% (6)
Fraction of executed direct-buy options (automated bidding agent) (%)	0.0015 (0.3830)	0.0053 (0.7280)	0.0096 (0.9778)	0.0014 (0.3728)	0.0045 (0.6672)	0.0106 (1.0275)
Fraction of executed direct-buy options (manual bidding) (%)	0.0145 (1.2041)	0.0221 (1.4876)	0.0282 (1.6802)	0.0144 (1.1983)	0.0298 (1.7268)	0.0392 (1.9826)
Average number of placed bids (automated bidding agent)	4.3813 (4.3226)	5.2359 (7.4805)	6.8607 (9.2563)	4.7931 (4.7375)	5.8543 (8.4688)	7.6568 (10.1796)
Average number of placed bids (manual bidding)	4.3813 (4.3226)	5.2319 (7.4540)	6.8134 (9.1907)	4.7931 (4.7375)	5.8504 (8.4607)	7.5980 (10.1168)
Number of pairs	6,613,218	6,829,613	8,095,428	215,873	224,633	274,653

Note. Standard errors are in parentheses.

our nonparametric matching model is less restrictive than our parametric approach, and, consequently, the conclusions based on this approach are more general (Siegel 1957).

Following Pope and Schweitzer (2011), we consider a matching model to compare participations with and without automated bidding agent usage where participants placed the same number of bids for the same product. We create a list of potentially irrational decision scenarios where participants placed their bids using an automated bidding agent. Next, we use a matching algorithm to identify potentially irrational decision scenarios where other participants placed the same number of bids for exactly the same product manually. For some scenarios we do not find any exact match, whereas for other potentially irrational decision scenarios we do. In the first case, we exclude this scenario from our analysis. In the latter case, we include each matched pair in our analysis.¹⁸

The results from our matched analysis are reported in Table 4. Column (1) shows the 6,613,218 pairs of potentially irrational decision scenarios, with and without an automated bidding agent, where we could find an exact match for the number of bids placed for the same product across auctions. Consistent with our hypotheses and our parametric results, for the same number of bids placed for the same product, the direct-buy option was executed significantly more often in potentially irrational decision scenarios where bids were placed manually (0.0145% of the participations

versus 0.0015% of the participations, $p < 0.000$). In columns (2) and (3), we report results from pairs of potentially irrational decision scenarios with and without an automated bidding agent where the numbers of placed bids differ by 5% and 10%, respectively. With larger differences in the number of placed bids, we increase the count of matched pairs, but these matches are obviously less precise. We find that manual bidders exercised the direct-buy option four and three times, respectively, more often than participants who used an automated bidding agent. By imposing an additional restriction consisting of matching only those decision scenarios where the respective participant placed the same number of bids for the same product in the *same auction*, we emulate column (1) in column (4) of Table 4. Applying the same restriction, we emulate columns (2) and (3) in columns (5) and (6), respectively, of Table 4. Reassuringly, we find that manual bidders exercised the direct-buy option between four and seven times more often than participants who used an automated bidding agent. Overall, the nonparametric results qualitatively mirror the results obtained from the main model.

6.4. Additional Robustness Checks

We conduct a wide range of further robustness checks and obtain qualitatively similar results. Our first check addresses concerns that some participants may lack sufficient knowledge of the pay-per-bid auction mechanism when participating for the first time. In particular, they may not really understand the mechanism of the direct-buy option, although all relevant information is publicly available before the auction starts. To address this issue, we drop each observation with no prior auction participation from our data set and reestimate our regression models on the resulting subsample. Our second check deals with the concern that, after executing the direct-buy option for the first time, a participant

¹⁸ Consider the following example: We identify a potentially irrational decision scenario where a participant places 10 bids for a specific product with an automated bidding agent. For the same product across different auctions, we find five potentially irrational decision scenarios where participants also place 10 bids manually. This results in five matched pairs (the automated bidding agent scenario matched to each of the manual bidding scenarios).

may internalize the extent of irrationality and, from then on, no longer repeat the same “mistake.” In such cases, subsequent auction participations would not lead to any direct buys irrespective of the bidding method used. We ensure the robustness of our results by restricting our analysis to observations of participants who never before executed the direct-buy option. We also check whether the sunk cost effect persists after an auction participant executed the direct-buy option by restricting our sample to those participants who executed the direct-buy option at least once before. In our third check, we use more precise controls for the end time of the auction. We split the day into four six-hour intervals and include three dummy variables controlling for the end time of an auction in our model. In the fourth check, we use different definitions for the usage of an automated bidding agent: in the first step, we include only observations where more than 90% of the bids were placed with one of the two bidding methods; in the second step, we increase this threshold to 100%; in a third step, we extend our main sample such that participations where a bidder placed fewer than or equal to 50% of the bids with an automated bidding agent are identified as manual bidding, whereas participations where a bidder placed more than 50% of the bids using a bidding agent are identified as agent bidding. Our fifth check addresses the additional concern that, although buyers might be aware of a potential lower price elsewhere, they nevertheless stick to our website because of potential fixed switching costs. One may argue that these costs are not a percentage of the product value, but a fixed nominal amount. We address this issue by including only those observations in our sample where the difference between the price on our website and the reference price was above €5. Our sixth check considers the potential effects of specific product categories influencing our results. In addition to the nonparametric matching approach, we address this issue by assigning each product to one of four product categories (home electronics, computers, videogames, and others) and include dummy variables for three of these categories in our model (*Computers Dummy*, *Videogames Dummy*, *Others Dummy*). Our seventh check considers bidders who just want to try out the auction website and place only very few bids. These bidders might execute the direct-buy option for other reasons than the sunk cost effect. We address this concern by including only bidders who placed more than 10 bids in an auction in our sample. Our results do hold for all of these robustness checks. Finally, all of our results are robust to random effects specifications (probit and logit), as well as linear probability model specifications (random and fixed effects).

7. Discussion and Conclusion

The advent of electronic markets has greatly increased opportunities for delegating decision making to IT.

Intelligent bidding agents on auction platforms (Adomavicius et al. 2009) or algorithms making their own decisions when trading on financial markets (Hendershott et al. 2011) are only some of the examples. It is surprising, then, that there has not yet been any theoretical or empirical research to date on how this delegation might affect human decision making and, especially, how it might influence critical human decision biases. This paper makes a first contribution toward filling this gap in the literature. We provide a general theoretical explanation of how behavioral sunk costs affect the occurrence of the sunk cost effect and why the delegation of decision making to IT is able to protect decision makers from these behavioral sunk costs. We empirically test our hypotheses in a pay-per-bid auction context. Our empirical analysis provides evidence for both the sunk cost effect for behavioral investments and for the role played by IT in significantly mitigating different contributors of these investments. Hence, through this mechanism, participants' IT usage significantly reduces the likelihood of the occurrence of the sunk cost effect. In economic terms, by mitigating different contributors of behavioral investments (e.g., time or effort), delegating to IT halves a bidder's total investment in an auction, thereby reducing the likelihood of the occurrence of the sunk cost effect by more than 50%.

With these results, we also contribute to the literature on the sunk cost effect. We are the first to observe behavioral investments in a real market setting and to analyze their role in the sunk cost effect. Our findings support the laboratory experiments of Cunha and Caldieraro (2009, 2010) and Navarro and Fantino (2009), who stated that even purely behavioral sunk costs can induce the sunk cost effect. Our findings also provide a first step toward generalizing earlier work on the effect of IT usage on decision biases to real market situations. Our results show that IT can alleviate the occurrence of the sunk cost effect in a real market situation. Further research is needed, however, to examine whether IT can also alleviate or even eliminate other decision biases in such situations. With regard to the different contributors of behavioral investments and their relative roles in the sunk cost effect, we have shown that time invested in the bidding process has only a comparably small impact on the occurrence of the sunk cost effect compared with other contributors of behavioral investments that are closely implicated in the placement of bids, such as the quasi-endowment effect. The detailed evaluation of the respective roles of different contributors of behavioral investments is an open topic for further research. Meanwhile, our results might help explain the contradictory experimental results for behavioral investments—mostly in the form of time—on the sunk cost effect.

The findings in this paper are robust and have survived a wide range of robustness checks. The data analyzed in our paper were provided directly by a website offering pay-per-bid auctions. Therefore, we are able to include a wide range of controls in our models. Additionally, our results remain qualitatively unchanged when we consider different reference prices for auction participants. We also consider the possibility that participants who use an automated bidding agent are self-selected, and therefore by identifying these participants and separating them from those who do not use an automated bidding agent, we provide additional reassurance on the robustness of our results. Thus, we find strong evidence for the effects described above.

Although the quantitative estimates from pay-per-bid auctions may not be directly applicable to other domains, our results are suggestive nevertheless. Because the delegation of decision making to IT has a statistically and economically significant impact on the occurrence of the sunk cost effect, behavioral sunk costs may have a much higher impact than prior research suggests. Further research is needed, however, to present additional evidence of this effect on other markets, in particular, experimental studies that randomly manipulate participants' behavioral investments. In this respect, and in light of the argument that participants on pay-per-bid auction websites are generally inclined to be risk seeking (Platt et al. 2013), our results can be seen as providing a lower bound for the effects discussed in this paper. Given that risk seekers should evaluate small losses less negatively than the risk-averse general public, their evaluation of behavioral sunk costs should also be less negative than that of the latter. In other words, compared to the observations in our sample, we would expect to find an even more pronounced effect of behavioral investments on the likelihood of the occurrence of the sunk cost effect in the general public. At the same time, the effect of IT usage on the different contributors of behavioral investment clearly is independent of an individual's risk perception. For example, delegating a task that lasts, say, two hours should save the same amount of time, irrespective of this person's risk preference. Thus, if behavioral investments are evaluated more negatively by the general public, and IT usage has a similar effect on the different contributors of behavioral investment, delegating to IT should have a more positive effect than for the average—risk-seeking—auction participant. Another factor that also suggests that our results are a lower bound for the discussed effects is that some auction participants, after losing in the auction, may purchase a product because of their sunk costs from other retail sites that we cannot observe. As we have shown in the paper, bidders in manual participations are more likely to be affected by the sunk cost effect. Thus, such unobserved irrational purchases, if any,

are more likely to occur after manual participations, and therefore the real effect of delegating to IT on the sunk cost effect may be even higher than our estimates suggests.

Another important dimension pertaining to the generalizability of our results is the degree of IT experience of the general public compared to participants on pay-per-bid auction websites. The positive and highly significant effect of the number of bidding agents configured provides a strong indication that the very process of delegating to IT may in itself contribute to behavioral investment. The total effect of IT usage on behavioral investment crucially depends, therefore, on the relationship between the inevitable behavioral investment necessary to delegate decision making to IT and the reduced behavioral investment caused by IT usage. If the reduction through delegation is lower than the behavioral investment required for delegation, it is possible that IT usage might even increase the likelihood of the occurrence of the sunk cost effect. Therefore, it is important for researchers and practitioners not only to provide ways and means of delegating to IT but also to ensure that these are easy to use so that they generate only negligible behavioral investments.

Our results are of particular interest to firms hosting online auctions. These firms need to carefully consider whether to provide bidding agents to increase customer satisfaction, or, conversely, not to provide such agents to increase profitability through the sunk cost effect. On the one hand, profitability may increase in the short term as a result of bidders in online auctions falling prey to the sunk cost effect for behavioral investments and, therefore, placing more and higher bids than they would otherwise have done, but over the long term, bidders may feel increasingly dissatisfied with the auction website and disengage as a result.

Understanding the impact of delegating parts of decision making to IT on the sunk cost effect also has more general managerial implications. Our study shows that the sunk cost effect is induced not only by monetary investments but also by behavioral investments. These investments can occur in a wide range of situations involving, among others, decisions about project investments, project management, policy making, trading on financial markets, as well as auction participations. For example, a manager might invest huge amounts of time and effort in evaluating potential project alternatives. Based on the theoretical mechanism described in this work, a manager would perceive the investment alternatives more positively compared to situations where she had not invested any behavioral resources in the evaluation process. If this person were to make decisions about investment alternatives, there may be a structural bias toward alternatives that require the highest evaluation effort. This bias could lead to substantial misallocations of capital due to the sunk cost effect. Therefore, decision makers should

scrutinize all types of decision situations very carefully with a view to the potential for sunk behavioral investments. Where there is an increased chance of substantial behavioral investments, managers should be aware that their decision making may be significantly affected by these investments. In these situations, it is important to ask themselves whether a decision could be different without such behavioral sunk costs. It may also be appropriate to consult a person who has not invested any behavioral resources or even to delegate the decision making to such a person. Furthermore, in some decision situations, the introduction of a software agent or another dispassionate advisor can detach decision makers from the decision-making process and, thus, protect them from behavioral investments. By purposefully reducing behavioral investments, this detachment has the potential to substantially increase the quality of decisions, hence providing decision makers with a competitive advantage. At the same time, the availability of appropriate software agents for a range of decision situations is currently limited. For this reason, the development of automated software agents able to protect decision makers from behavioral investments in various decision situations should become an important goal for practitioners and researchers from the information systems discipline.

One limitation of our study lies in our inability to fully disentangle the effects of the different contributors of behavioral investments on the sunk cost effect. Despite this limitation, our results from the alternative operationalizations of behavioral investments suggest that time invested in the bidding process constitutes only a smaller part of a bidder's total behavioral investment. One interesting area for future research would be to identify other important factors contributing toward behavioral investment and to quantify their relative effects on the sunk cost effect. Finally, we restricted our analysis to only one decision bias. Another important area for future research is to analyze whether IT usage can mitigate or even eliminate other decision biases in real-world situations.

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