EXPECTATION, DISAPPOINTMENT, AND EXIT: EVIDENCE ON REFERENCE POINT FORMATION FROM AN ONLINE MARKETPLACE[1]

Abstract

We study disappointment and platform exit among new bidders in an online auction marketplace. In particular, we study a hybrid auction format with a "Buy-It-Now" option which, when executed, will abruptly end the auction and cancel any standing bids. When this happens, if the formerly leading bidder is new to the platform, then they are 6 percentage points more likely to exit the marketplace for every additional day they spent in the lead. This is rationalized by disappointment-averse bidders with outside options and rational expectations about the likelihood of winning. Our explanation is validated by three ancillary predictions: when expectations are lowered by higher competing bids, there is no effect; sensitivity of exit is declining in prior experience, and, for bidders who do not exit, time in the lead during the first experience predicts a subsequent preference for fixed-price, rather than auction, listings.

JEL Codes: D03, D47, D83.

1. Introduction

The framework of prospect theory and reference-dependent preferences developed by the seminal work of Kahneman and Tversky (1979) has offered intuitive hypotheses for a number of so-called "behavioral" puzzles, from loss aversion to the endowment effect. To the canonical model of preferences it adds a *reference point*, a degree of freedom that distinguishes between a gain and a loss, elation and disappointment.

Moreover, if behavior in real markets mirrors the array of biases found in the lab—an important and open area for empirical work—then reference points matter for the way practitioners make policy, manage firms, and design markets.

But where do reference points come from, and how can they be manipulated? This question is basic to both the positive and the normative implications of the theory. Kahneman and Tversky (1979) are ambivalent on this point; they mostly focus on the status quo as a reference point, but they also suggest that expectations may play a role. Following a line of thought that takes expectations as reference points (Bell, 1985; Loomes and Sugden, 1986), Kőszegi and Rabin (2006) propose an elegant framework in which reference points are given by rational expectations of equilibrium outcomes, engineering reference points that arise naturally and endogenously within the context of the application. However, as they acknowledge, this framework is motivated as much by the need to discipline the model as by realism, for want of germane empirical evidence from market behavior.[1] The next step of building a practical theory of reference-dependent preferences, relevant for market design and policy analysis, relies on the empirical challenge of understanding reference point formation in context, *i.e.*, in real market behavior.

1. "...research on the nature of reference points themselves is quite limited. While we hope that experiments and other empirical work will shed light on this topic, our model makes the extreme assumption that the reference point is fully determined by the *expectations* a person held in the *recent past*" (p. 1141, emphasis original). Subsequent examples of experimental work on this topic, which we view as complementary to our endeavor, include Ericson and Fuster (2011) and Gill and Prowse (2012).

This paper studies reference point formation and disappointment aversion using rich data from eBay's auction marketplace, which gives us leverage on the difficult empirical task of teasing out variation in reference points. We show how disappointment from losing an auction, driven by variation in the expected probability of winning, affects a bidder's likelihood of abandoning the auction platform. The data support two critical ingredients of the expectations-as-reference-points approach. First, a bidder should rationally expect a higher likelihood of winning the longer she is in the lead. Second, expecting a higher likelihood of winning makes an abrupt loss more disappointing, reducing the perceived benefit from participating in the auction platform, which in turn leads to exit.

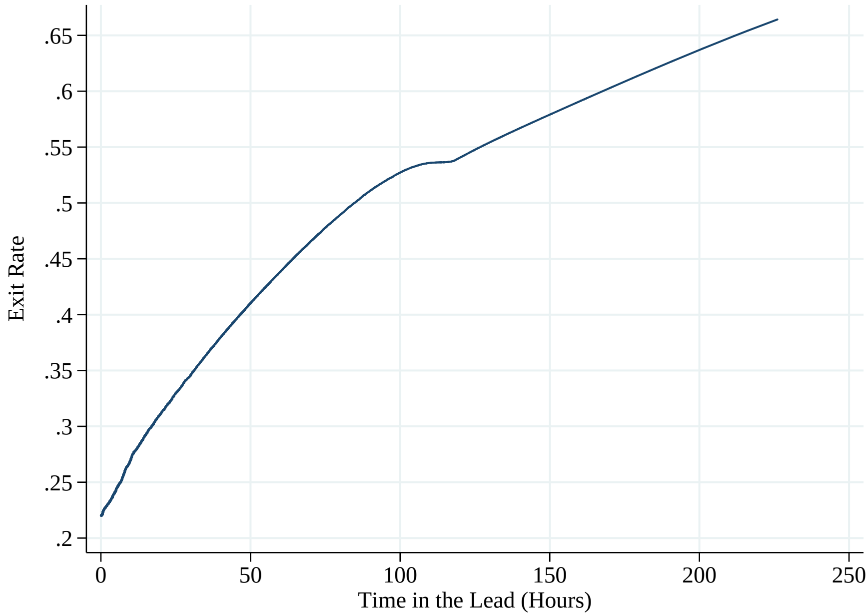
Using observational data to study reference point formation presents two salient measurement problems: finding an observable reference point "shifter" and measuring *ex post* disappointment. With those two challenges in mind, we use data from eBay's hybrid Auction/Buy-It-Now (ABIN) sales format. These auctions proceed similar to the standard ascending auctions on eBay, but potential buyers may execute the Buy-It-Now (BIN) option and cancel the auction immediately to purchase the item at the pre-specified, publicly listed BIN price set by the seller. For example, suppose person A chooses to place a bid in the auction and is the current high-bidder. At some later point, while A is still the high bidder, person B arrives and selects to buy the good at the Buy-it-Now price by clicking the BIN button. This action immediately ends the auction; B gets the good and A gets nothing. Importantly, A has no opportunity to counter or raise their bid in response. We will refer to this event as a "BIN event." In the ABIN setting we construct a dataset of first-time bidders who hold the standing high bid in an auction but lose abruptly to BIN events. Using this sample, Figure 1 depicts the central stylized fact: new bidders who hold the lead for longer are substantially more likely to exit the auction platform after the auction is canceled. In Section 5 we show that this result is robust to extensive controls, including the timing and level of the bid.[2] Controlling for the time at which A's bid is submitted, time in the lead in a BIN-terminated ABIN auction is determined by the arrival of the competing buyer B who chose the BIN option. This gives us plausibly exogenous variation in the reference points shifter.[3]

To rationalize the stylized fact depicted in Figure 1, Section 3 presents a simple model and derives hypotheses based on disappointment-averse bidders with reference points formed from rational expectations about the likelihood of winning. To this we add an assumption that is consistent with a simple form of learning about the value that the auction platform provides participating bidders. We predict that, when an auction is abruptly canceled, new bidders who have held the high bid for longer will

2. Though these controls are imperfect proxies for bidders' unobserved types and information, the robustness of the results to additional covariates is informative about the character of the endogeneity one would require to overturn the qualitative findings (Altonji et al., 2005; Oster, 2019), an argument we formalize in Appendix A.

3. The challenge of finding reference point shifters is not the relevance of shifting expectations, but the exogeneity of such shifters. In our setting there are many credibly relevant alternatives for reference point shifters—the level and timing of the bid, for instance—but most of these are either known to or chosen by the bidder themselves, and therefore endogenous to the exit choice.

FIGURE 1. Exit Rate by Time in the Lead



Notes: This figure presents a LOWESS plot of the exit decision of first-time bidders in our sample against time spent in the lead, in hours, prior to the BIN event which closed the auction. See Section 4 for details on sample construction and Section 5 for results robust to extensive controls.

suffer greater disappointment than those who held it only briefly. This is because their reference point shifts over time as they hold the highest bid; they come to *rationally* expect a higher probability of winning the auction—an expectation that is consistent with the data.[4]

4. A literature on Decision Affect Theory in psychology posits a role for counterfactual thinking in emotional responses (Mellers et al., 1997). With respect to that literature, our results favoring expectations-based reference points suggest that the significance of counterfactuals in responses depends on the probability that agents place on them (Shepperd and McNulty, 2002)—probabilities which in our setting qualitatively match rational expectations.

In turn, bidders who suffer greater disappointment in their first interaction with the platform update negatively about the value of revisiting it. Therefore the longer they hold the leading bid before the auction is canceled, the greater the disappointment, and the more likely they are to abandon the platform altogether. This story rationalizes the positive correlation between time as the winner and the exit rate shown in Figure 1, and offers other testable predictions that help us rule out alternative stories.

A natural alternative explanation for our findings is that bidders suffer from a form of the sunk cost fallacy: neglecting that the time spent on the first auction is sunk, they might decide that winning the good is not worth the cost of participating *twice*. In this way, being irritated by the time wasted, and in proportion to time wasted, might drive exit from the platform. To reject this alternative narrative, we construct a placebo sample of first–time bidders whose expectations are lowered due to competition from other bidders—that is, they are outbid and ultimately lose, but they had ample time to raise their bid. An implication of our framework is that, although these bidders have the same *material outcome*, they do not suffer disappointment because they had the option to re–bid, and so anticipate loss when they chose not to re-bid. Therefore we predict that they are insensitive to time spent in the lead. This is confirmed empirically in our placebo sample.

Though our main result is that time in the lead is correlated with not returning to bid in another auction, we also validate that this is robust to not returning to the eBay platform at large (*i.e.*, including non-auction, fixed-price listings). A secondary result is that conditional on returning to the eBay platform for any kind of activity, time in the lead is correlated with a smaller likelihood of participating in auctions compared to fixed-price listings. That is, among bidders who do return to eBay, those who suffered more disappointment are more likely to avoid auction format listings of the platform. The data confirm this hypothesis.

Our proposed explanation also makes predictions about how BIN events affect more experienced bidders. Bidders return to the site if the expected surplus from doing so exceeds the value of their outside option. Experienced bidders have less variance in their prior beliefs about future surplus, so they update less severely on a negative experience. Moreover, they are selected on survival, which implies that they are likely to have a worse outside option. Therefore we predict that while time spent in the lead before a BIN event may affect their exit rates, they will be less sensitive than for new bidders. The data confirm this hypotheses. This result is related to arguments that experienced market participants are less likely to display behavioral biases (List, 2003), but with an important difference in interpretation. Our explanation does not require that experienced traders have different *preferences* from inexperienced ones—rather, it explains why nonstandard preferences are less likely to be *expressed* in the case of experienced participants.

Barberis (2013), reviewing three decades of research on reference-dependent preferences, argues that outside the areas of choice under uncertainty, namely finance and insurance, a lack of empirical analyses casts doubt on the relevance of reference points, and prospect theory more generally. This is a gap that our paper helps fill. Closest to our work is Card and Dahl (2011), who study the relationship between family violence and losses by the home football team, finding that the latter contributes only when the loss is unexpected, as measured by betting markets. In addition Post et al. (2008) studies reference points in a game show, Pope and Schweitzer (2011) in golf, Rees-Jones (2018) in tax sheltering, and Allen et al. (2017) in marathons. Like all empirical work on reference points, including our own, these papers seek identification in narrow settings, raising concerns of external validity. This is exacerbated by the fact that they all find identification in non-market settings. In contrast, we study market behavior, a domain in which documentation of reference points tends to be indirect, *e.g.*, the long series of papers concerning the labor supply of NYC taxi drivers, where reference points are mediated through an additional hypothesis of wage and time targets (Camerer et al., 1997; Crawford and Meng, 2011; Farber, 2015).[5]

5. Our work is also related to the idea of a "quasi-" or "pseudo-endowment" effect (Ariely and Simonson, 2003; Heyman et al., 2004; Wolf et al., 2005; Bramsen, 2008; Cotton, 2009). Where the classical story for the endowment effect distinguishes between possession and non-possession, these models allow for an intermediate range. Bramsen (2008), it is based on expectations, as in the mechanism we describe. Alternatively, Heyman et al. (2004) it is based on gradual membership. We will not be able to distinguish between these hypotheses, as they are equivalent in our setting. However, for binary possession, Heffetz and List (2014) offer an experimental disambiguation of expectations and assignment as an explanation for the endowment effect, and find evidence for the latter.

In a recent contribution to that literature, Thakral and Tô (2021) estimate a structural model of the taxi driver's problem that nests a continuum of models of reference point formation. Their results favor what they call adaptive reference points, which incorporate information continuously but with a lag. As in prior work on the topic, the narrowness of our environment is a deliberate choice—identification at the cost of external validity—however, we believe that we complement prior work by offering a rare example where we can cleanly identify reference points in observational data from actual market behavior.

Finally, though our primary interest is the documentation of reference point formation, our results also have implications for market design in online platforms. Analogous to the discussion of car dealers "throwing a lowball" offer in Kőszegi and Rabin (2006), employing allocation mechanisms that risk leaving consumers in the "domain of losses," *i.e.*, disappointed vis-à-vis their reference point, can cause attrition from the platform. This is particularly important for platforms because they face economies of scale via network effects. These effects are strongest for newer bidders to the platform, which is intuitive: these bidders are still engaged in learning to use the platform and forming expectations. Platforms should be wary of user experiences that encourage unrealistic expectations; disappointed consumers may leave the site entirely. It may be worthwhile to curate the experience of new users on a platform because loss alone does not cause disappointment and exit; consumers who expect to lose do not demonstrate the higher likelihood of exit, even though, in our sample, they share the same material outcome: they go home with nothing.

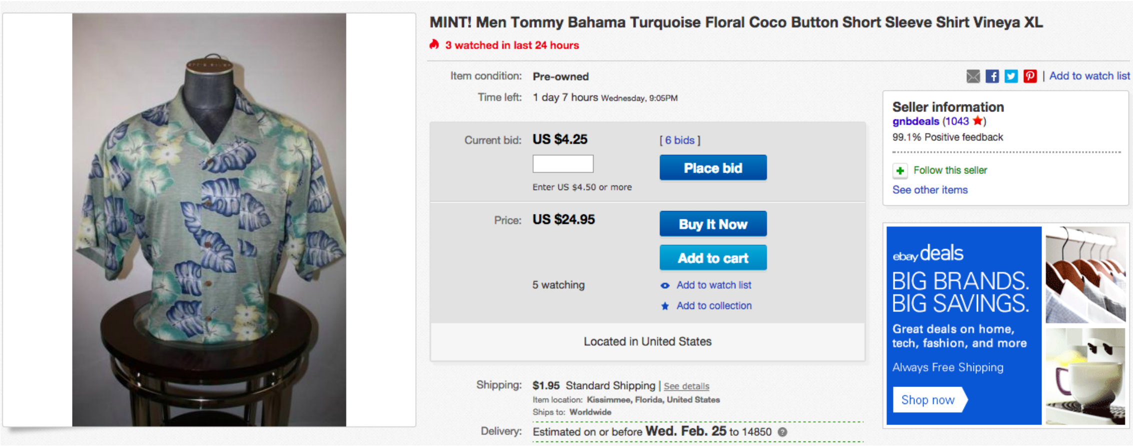
2. Empirical Setting

We examine Auction/Buy-It-Now (ABIN) listings on eBay.com, a subset of the auction listings in which a seller has elected to add the Buy-It-Now (BIN) feature. In a standard auction listing, the seller specifies the auction's duration and the bidder with the highest bid at the end wins, paying the second highest bid plus an increment. In an ABIN listing, the auction proceeds similarly but the listing has a BIN button with a specified list-price, and potential buyers can execute the BIN option by clicking the button to immediately end the auction and purchase the item at the BIN price. ABIN listings accounted for about one quarter of all auction listings on eBay at the time of our analysis. Figure 2 presents an example of an ABIN listing—buyers can either bid (by clicking on the "Make Bid" button) or execute the BIN option (by clicking on the "Buy-It-Now" button). In the latter case they will purchase the item at the BIN price of $24.95.

The BIN option may disappear in the course of the auction. For the product categories in our data, it disappears when the standing price exceeds 50% of the BIN price.[6] Ignoring bidding increments, this will occur only if there are two bidders who have each placed a bid that is at or above 50% of the BIN price. If only one bidder

6. The standing price is the "Current Bid" in Figure 2 ($4.25). Note, however, that the standing high bidder may have submitted a substantially higher, still private, proxy bid. In this case the site will bid on her behalf, up to the amount of the proxy bid, should other bidders enter. In categories other than the four we consider the BIN option disappears once any bid above the secret reserve has been submitted.

FIGURE 2. Example of an ABIN Listing



Notes: This is the listing page for an example ABIN listing. In addition to the "Place Bid" button, which is standard for auction-style listings and does not change the ending time, the buyer can use the "Buy-It-Now" option and purchase the good, closing the listing immediately. The current standing high bidder has no recourse when the BIN option is exercised.

entered a bid that is higher than 50% of the BIN price, then the standing price will be lower than 50% of the BIN price, and the BIN button will still remain. When the BIN option is exercised, the bidder with the standing high bid will be notified that the auction ended, and that her bid was unsuccessful.

Sellers on eBay choose from a variety of mechanisms when they create a listing.[7] Budish and Takeyama (2001) argue that offering a BIN option may allow sellers to extract more revenue from risk-averse buyers; relatedly, Ackerberg et al. (2017) identify risk preferences as well as discounting preferences from the bid-or-BIN

7. These are auctions (with or without a BIN option) or fixed price format (with or without a bargaining option). Minor options include duration, starting price, secret reserve price, end time, and shipping terms.

decision faced by bidders who arrive at a listing. Many other conjectures have been put forward to explain the use of the ABIN mechanism, from reference-dependent preferences to common-values concerns; see Bauner (2015) for a recent survey of this still-lively literature as well as a structural model of mechanism choice. For our application we take the set of ABIN listings as given, though we acknowledge that there may be substantial selection of listings into the ABIN mechanism. This is an external validity concern. We note, however, that buyers cannot explicitly condition on the availability of a BIN option among auctions when using the website's built-in search feature.

3. Theory and Hypotheses

Figure 1 documents the basic stylized fact—that among first-time bidders who hold the standing high bid when an auction is canceled, there is a strong positive correlation between time in the lead and exit. In this section we present a simple behavioral model in which time in the lead is a proxy for the optimism of bidders' expectations; expectations that, when disappointed, predict exit from the platform. We develop the model in two steps. First, we characterize disappointment aversion for bidders with rational expectations reference points in an ascending price auction. Second, we model bidders' exit choices in which they weigh revisiting the platform against an outside option, and update negatively on future expected surplus when they have negative experiences on the platform.[8] This second component of our model augments the reference-dependence part of the model in the same way that the choice of domestic violence augments the reference-dependence model in Card and Dahl (2011).

3.1. Disappointment Aversion and Reference Points

A bidder holds the standing high bid in an ascending price auction. If she wins at the end of the auction then her surplus will be the difference between her valuation and the second-highest bid. Letting $S \geq 0$ denote the expectation of this difference, conditional on winning, her realized utility from the auction, π, is given by

$$\pi = Sy + \mu(Sy - Sp), \tag{1}$$

where y is an indicator variable equal to 1 if the bidder wins and 0 otherwise, and p is the bidder's expectation of y, held at the time the auction ended. This expectation p is her reference point over the probability of winning, and μ represents her final utility function, *i.e.*, incorporating reference points, as in Shalev (2000). If $\mu(\cdot) = 0$, then bidders have classical preferences; alternatively, if $\mu(\cdot) \neq 0$, then bidders care about deviations from expectations. For simplicity, let μ be piecewise linear, so that

8. We are *not* attempting a full dynamic model of strategic bidding in ABIN auctions with disappointment aversion and endogenous reference points as this would involve technical challenges well beyond the ambition of this empirically-oriented paper. See, *e.g.*, Nekipelov (2007) for an introduction to the technical challenges of within-auction dynamics under rational expectations.

$$\mu(x) = \begin{cases} \alpha x & \text{if } x \leq 0 \\ x & \text{if } x > 0. \end{cases}$$

The bidder's preferences exhibit *disappointment aversion* if $\alpha > 1$. In the empirical section we focus exclusively on losing bidders, *i.e.*, the region where $y = 0 \leq p$, and we compare bidders with identical outcomes, but different reference points p.[9]

Let $t = 0$ denote the beginning of an auction and $t = 1$ its end, and let $p(t)$ denote the high-standing bidder's expectation of winning (y) for any time $0 \leq t \leq 1$ during the auction. We assume that bidders who hold the high bid grow progressively more convinced that they will win, *i.e.*, $p(t)$ is strictly increasing in t. Intuitively, as time goes by, competing bids are less likely and the leading bidder should rationally believe that they are more likely to win. Indeed, what we take as an assumption is a generic result of micro-founded continuous-time auction models with Poisson arrivals of bidders (Ambrus et al., 2014; Hopenhayn and Saeedi, 2016; Kapor and Moroni, 2016).

9. A more subtle distinction between disappointment aversion as formulated in Loomes and Sugden (1986) and reference-dependence as in Kőszegi and Rabin (2006) concerns whether the referent is the certainty equivalent or the entire distribution of outcomes. Sprenger (2015) explores this distinction experimentally and finds evidence for a risk endowment effect, consistent with the latter. Unfortunately our empirical setting does not offer any further leverage on the distinction.

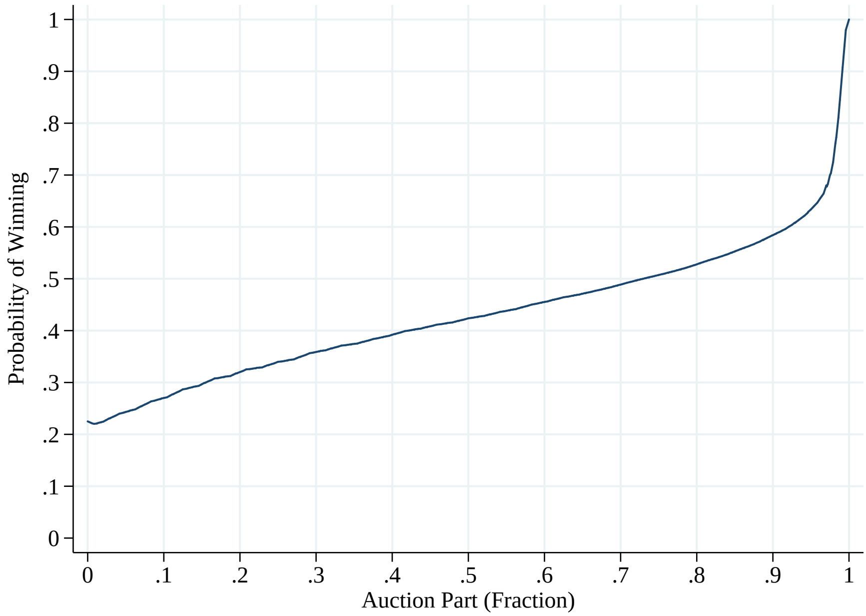
In fact, this growing optimism is not only a natural theoretical construct but is also consistent with our data from ABIN auctions. Figure 3 depicts the empirical likelihood, drawn from our sample of ABIN auctions, that a bidder who holds the standing high bid at any particular time t goes on to win the auction. Hence, bidders' shifting reference point $p(t)$ aligns with rational expectations, in the spirit of Kőszegi and Rabin (2006).[10]

As we are interested in disappointment aversion from losing an auction, note that there are three ways that a bidder in the lead can lose an auction. The first is when she is outbid early enough during the auction and she chooses not to re-bid, therefore accepting and anticipating the loss perfectly and resulting in beliefs $p = 0$ at the end of the auction. In the second scenario, she loses at the end of the auction because she is "sniped" by another last-minute bidder leaving her no time to bid in response, and her belief is $p = p(1)$. Indeed, sniping occurs with some regularity on eBay and so we allow for the possibility that $p(1) < 1$ precisely because a bidder may get sniped in the last minute.[11] The third and final scenario allows for the possibility that another bidder executes the BIN option, ending the auction at a time $t < 1$ for which, like

10. Note that while we follow Kőszegi and Rabin (2006) in formulating reference points from rational expectations, our hypothesis builds on disappointment aversion, following Gul (1991), rather than loss aversion.

11. See Roth and Ockenfels (2002) and Bajari and Hortaçsu (2003) for evidence on the causes and prevalence of sniping, and Backus et al. (2015) for evidence on its effects on platform exit. Much of this sniping happens in the last seconds of an auction, too late for any feasible response, and so we treat $t = 1$ qualitatively different from being outbid at $t < 1$.

Figure 3. Empirical Likelihood That Current Leading Bidder Wins Auction



Notes: This figure presents the empirical likelihood that the bidder who holds the current high bid at time t ultimately wins the auction. Note that t is normalized such that an auction begins at $t = 0$ and ends at $t = 1$. To construct the plot we take, for each point t, the set of bidders who were currently in the lead in each of our auctions and compute the average value of a dummy variable for whether they were the *eventual* winner at the end of the auction. The figure presents a LOWESS plot of that dummy variable over t. We use all auctions in the four ABIN categories during our sample period.

in the sniping scenario, our bidder has no recourse and her beliefs at the end of the auction are $p = p(t)$. Hence, we summarize our assumptions on the evolution of p as follows:

Assumption 1 (Evolution of p). *$p(t)$ is strictly increasing in t. Moreover,*

$$p = \begin{cases} 0 & \textit{if bidder } i \textit{ is outbid and does not re-bid at } t < 1 \\ p(1) \leq 1 & \textit{if bidder } i \textit{ holds the high bid at } t = 1 \\ p(t) < p(1) & \textit{if bidder } i \textit{ loses to a BIN event at time } t < 1 \end{cases}$$

Note that we posit a substantive difference between bidders who are outbid and can choose to re-bid but don't, and those bidders who lose to a BIN option. The former have *recourse*, *i.e.*, the option to re-bid, while the later are hit with the surprise of losing with no recourse. By assuming that surplus is evaluated at the end of the auction, then bidders who lose to another bid suffer no disappointment because—unlike those who lose to a BIN event—conditional on losing, they anticipate loss. This is related to the finding of Filiz-Ozbay and Ozbay (2007) that bidders have no regret in standard second-price auctions. In this sense our setup implicitly draws on a notion of regret. A more comprehensive formal treatment would require a unified theory of regret and disappointment, which to our knowledge does not exist.[12]

12. From Loomes and Sugden (1986), p. 281: "Because regret theory makes comparisons across actions but within states of the world, it can predict violations of the transitivity axiom but not violations of the sure-thing principle; whereas disappointment theory, which makes comparisons across states of the world but within actions can predict violations of the sure-thing principle, but not violations of transitivity. However, both theories generate many of the same predictions such as the common consequence and common ratio effects in the case of statistically independent prospects, simultaneous gambling and insurance, and the isolation effect. Given the similarity of

3.2. Platform Exit

We now connect disappointing outcomes to platform exit. We assume that after engaging in an auction, bidder i updates her belief about the value of participating in future auctions and will exit the bidding platform whenever her expected utility of participating, given prior experience, is less than her outside option, θ_i,

$$\mathbb{E}[\pi_{m+1}|\pi_1, \dots, \pi_m] \leq \theta_i. \tag{2}$$

The expectation $\mathbb{E}[\cdot]$ is taken with respect to bidder i's subjective beliefs about the benefit of participating in another auction. θ_i is the value of her exogenous outside option, and is a bidder-specific random variable with distribution $F(\cdot)$.[13] We assume that bidders' expectations about future values of π are monotone in prior realizations. Formally,

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the fundamental structure of both theories, there may be grounds for thinking that a more general theory of rational choice under uncertainty may encompass both regret and disappointment."

An alternative, and for our purposes equivalent, explanation would be that since bidders who have the opportunity to re-bid are making a choice not to, the new reference point (that is, expecting to lose) "sinks in," in the sense of Heffetz (2021) before utility is evaluated.

13. The heterogeneity in outside options is behind Hypothesis 3, which implies that bidders who survive longer must be those with worse outside options. An alternative source of heterogeneity can be in the degree of disappointment aversion. That is, those who are less sensitive to disappointment are more likely to return, just like those with worse outside options.

Assumption 2 (Beliefs). $\mathbb{E}[\pi_{m+1}|\pi_1,\ldots,\pi_m]$ *is strictly increasing in* π_k $\forall k = 1,\ldots,m$.

This assumption implies that a bidder who obtains less surplus in any prior transaction, holding all else constant, is strictly less likely to revisit the site. We believe that this is uncontroversial, however disambiguating its theoretical foundations—whether rational updating on unobservables of the platform or, perhaps more plausibly, misattribution in the spirit of Bushong and Gagnon-Bartsch (2016)—is beyond the empirical ambition of this paper, and so we remain agnostic.

A natural interpretation of this assumption is that bidders are engaged in reinforcement learning, *i.e.*, that they view the platform as a black box, and update beliefs about future surplus in a way that is monotone in today's surplus. Similarly, they will update negatively on the expected surplus of returning to the platform when they have a bad experience. This draws a connection between disappointment—as determined by bidders' evolving reference points—and platform exit.[14]

14. A substantial body of prior work has used platform exit as a proxy for outcomes. Ascarza et al. (2016) show that recommendations for consumers who make suboptimal bundle choices on a platform can cause exit and conjecture that the recommendations make expenditures more salient. Israel (2005) uses customer retention in auto insurance to identify learning events for an experience good, and Ho et al. (2017) use price changes and expensive medical events as price salience shocks to study substitution between health insurance plans and, in turn, the pricing of those plans. On the eBay platform Backus et al. (2015) showed that first-time bidders are substantially less likely to return to the platform when they are "sniped," *i.e.*, lose to a last-minute bid, and Nosko and Tadelis

3.3. Empirical Predictions

Our main hypothesis combines disappointment aversion with platform exit and rationalizes our finding from Section 1:

Hypothesis 1. *The longer a first-time bidder has been in the lead, the more likely she is to exit the platform after an auction ends with a BIN event.*

For first-time bidders who lose to a BIN event, the probability of exit is given by $1 - F(\mathbb{E}[\pi_2|\pi_1])$, with $\pi_1 = \alpha S(y - p(t))$. By Assumption 2, $F(\mathbb{E}[\pi_2|\pi_1])$ is increasing in π_1, and by Assumption 1, $p(t)$ is increasing in t. Therefore the probability of exit is is increasing in t.

Our model yields three additional hypotheses.

Hypothesis 2. *Among first-time bidders who expect to lose at the end of the auction,* i.e., *who are outbid, have the opportunity to re-bid, and choose not to, time spent in the lead is unrelated to exit.*

For these bidders, $p = 0$ and therefore our model predicts that the probability of exit,$1 - F(\mathbb{E}[\pi_2|0])$, is invariant to time spent in the lead.[15]

(2015) and Masterov et al. (2015) use buyer exit to measure the quality of competing measures of seller reputation.

15. The condition that they have "the opportunity to re-bid" rules out the case where the bidder is "sniped." Our model implies that sniped bidders will suffer disappointment, and that this may

Hypothesis 2 helps to address alternative stories that depend on time spent in the lead but are not tied to disappointment. For instance, perhaps bidders update negatively in proportion to–and because of–time wasted on an unsuccessful bid. The comparison to a bidder who had an opportunity to re-bid and chose not to helps us isolate the role of reference points. We think of this hypothesis as a variation on a placebo test: we predict no disappointment for these bidders, *even though they have the same material outcome*. It jointly tests the claim of disappointment aversion as well as the ability of bidders to update their reference points when outbid.

HYPOTHESIS 3. *Among experienced bidders who lose following a BIN event, the relationship between time spent in the lead and exit is weaker than for inexperienced bidders.*

This follows from selection on survival: repeat bidders are likely to have worse outside options, θ_i. For bidders who are experienced, we have a long sequence of bounds on the value of their outside option. Therefore θ_i is negatively selected on survival. Formally, the probability that they exit is given by

$$\max\{0, \Big(F(\max_k\{\mathbb{E}[\pi_{k+1}|\pi_1, \ldots, \pi_k]\}) - F(\mathbb{E}[\pi_m|\pi_1, \ldots, \pi_m])\Big)\}. \tag{3}$$

be correlated with time in the lead. However, as explained in Footnote 22, we do not pursue this implication.

This expression is equal to zero if the bidder is inframarginal—that is, if her beliefs are no worse than the worst they have been before—and positive if the bidder's expected surplus reaches a new low. As an alternative motivation, if we were to assume that bidders are Bayesian, then the variance on their posterior beliefs about π_{m+1} will shrink as $m \to \infty$, so they update less (and are therefore less likely to exit) with each additional data point.

HYPOTHESIS 4. *Conditional on returning to eBay for any kind of activity after a first auction ended in a BIN event, time in the lead is positively correlated with a smaller likelihood of participating in auctions compared to fixed-price listings.*

Recall that eBay offers both auctions and fixed-price listings, so bidders who experienced disappointment in their first auction may still choose to return to eBay for the less risky prospect of buying items at their list prices. Namely, because losing to a BIN event reduces the expected value of auctions and *not* that of fixed-price listings, then for those bidders who do not abandon eBay altogether, a higher level of disappointment should lead bidders to shy away from auctions more than from fixed-price listings.

We conclude with a brief remark on the fact that the empirical content of disappointment aversion is sensitive to alternative specifications. These alternative specifications reflect basic questions about the nature of reference points. For example, how quickly do bidders update reference points? Hypothesis 2 would be false if bidders did not update their reference points when outbid, because then they too would suffer disappointment, and that disappointment would be correlated with the time they spent in the lead prior to being outbid. Relatedly, over what time span is disappointment evaluated? In our framework, it is over a single auction. Alternatively, if disappointment is evaluated over a longer time horizon, then perhaps bidders who suffered vis-à-vis expectations in one auction are more—rather than less—likely to revisit the platform and bid aggressively, in order to avoid the disappointment. This would reverse the prediction of H1—bidders at risk of disappointment would be more, rather than less, likely to return, and may bid more aggressively. To derive our hypotheses we have had to take a stand on these assumptions, and therefore any empirical test is not merely a test of the relevance of reference points in platform economics, but also a joint test of our specification of reference points. By adopting our particular assumptions, we not only rationalize Figure 1, but also generate additional testable hypotheses that we take to the data.

4. Sample Design

We construct our sample using all new users who created an account on the U.S. eBay site between June 1, 2009 and October 31, 2013 and confirmed their account through e-mail verification. From this set, we select users whose first non-browsing consumer action was casting a bid in an ABIN auction. We focus on first-time bidders because, as our framework posits, these are the set for whom exit is most responsive to disappointment. We relax this restriction later to test Hypothesis 3.

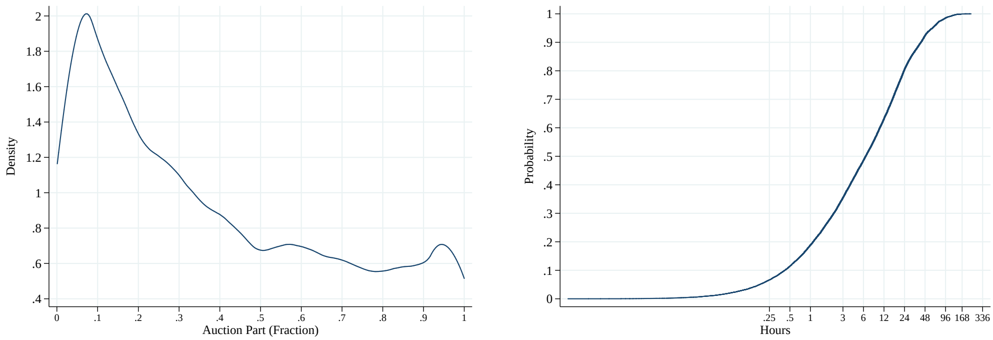
We further limited the sample to auctions belonging to four specific product categories: cell phones and accessories; clothing, shoes and accessories; event tickets and experiences; and motor parts and accessories. These were chosen because therein the BIN option remains available until the standing price exceeds 50% of the BIN price. In other categories, the BIN option disappears once the first bid is placed.[16] We then restrict attention to successful auctions where there were at least two participants. For each auction that closed prematurely through the BIN option, we retained a *single* losing bidder: the one who was leading at the time the BIN option was exercised and was also a first-time bidder.[17] This reduces the sample to 23,439 first-time bidders who lost when the auction was canceled due to a BIN event.

There is substantial variation in the timing of these BIN events, both in relation to the auction clock and with respect to the length of time that the losing bidder was in the lead. Figure 5a shows the distribution of when the BIN option was exercised. Because auctions vary in length, we normalized the timing by the intended duration so that 0 corresponds to the beginning and 1 to the scheduled end. Figure 5b shows the empirical CDF of time in the lead in hours. The median bidder is in the lead for approximately 6 hours, but there is a substantial right tail of bidders who lead for significantly longer periods of time. The average "time in the lead" for a bidder was just under 15 hours.

16. If there is a secret reserve price, the BIN option lingers until a bid exceeds it. In all categories other than vehicles, the BIN price must always be at least 30% higher than the starting price.

17. We relax this restriction later to test Hypothesis 2.

FIGURE 4. Variation in Timing of the BIN Event



(A) Distribution of BIN Option Use (B) Empirical CDF of Time in the Lead

Notes: Panel (a) presents a kernel density plot of the times at which the BIN option was exercised in our sample, normalized by the length of the auction to a [0,1] scale. Panel (b) presents the empirical CDF of time spent in the lead by bidders in our sample in $\log_2$ hours. For example, the median bidder who loses to the execution of the BIN option spent six hours in the lead.

For each losing bidder, we construct our primary outcome variable, "exit," as a dummy for whether the losing bidder ever participated in another auction within 365 days of her loss. 72% of new bidders who lost via BIN returned to bid in another auction within a year. An auction here means any auction on the platform, whether ABIN or otherwise, and in any category. This rate may not be representative of the platform at large, since the bulk of these auctions are for phones and clothing.

We also obtain data on the timing and levels of bids, demographic characteristics, as well as the characteristics of the auction and the seller.[18] On average, there are 95 hours of scheduled time remaining in the auction when the BIN event occurs. Items being auctioned are 42% new and are mostly split evenly between clothes and phones, with only 8% of the sample in auto parts and tickets. The joint coverage of

18. Detailed summary statistics on these controls are shown in Appendix Tables A.1 and A.2.

the demographic data, detailed in Appendix A, limits the sample to 12,068 bidders, which we use for some specifications that control for demographic characteristics. Bidders for whom we have demographics in this sample are 62% female and generally young with a wide distribution of incomes.[19]

5. Results

5.1. H1: Expectation, Disappointment, and Exit

Recall that Figure 1 documented the probability of bidder exit by hours spent in the lead for a sample of first-time bidders who lost when the auction was canceled due to a BIN event. We found a positive relationship between time in the lead and the likelihood of exit that is consistent with disappointment aversion and rational reference point formation. Absent any confounds, Figure 1 is evidence for Hypothesis 1: the longer a bidder maintains the standing high bid before a cancellation, the more likely they are to exit. However, there are many omitted variables driving exit that could be correlated with variation in time in the lead. Mechanically, that variation comes from two sources: the time at which the bid is placed and the time of the BIN event. While the former is clearly endogenous, we posit that the latter source of variation is exogenous—we see no reason to believe that the buyer exercising the BIN option does so in a way that is correlated with the likelihood that the current high

19. Note that this sample is not representative of the eBay users in general because it is for a select set of categories and conditional on a BIN event occurring and consists of new users only.

Table 1. AME of an Additional 24 Hours in the Lead on Exit

	(1) AME	(2) AME	(3) AME	(4) AME	(5) AME	(6) AME
Time in the Lead (24 Hours)	0.073***	0.069***	0.065***	0.067***	0.064***	0.064***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
Bid-Bin Ratio and Spells		Yes	Yes	Yes	Yes	Yes
Auction Attributes			Yes	Yes	Yes	Yes
Time Variables				Yes	Yes	Yes
Site Visits					Yes	Yes
Demographics						Yes
N	23,439	23,439	23,439	23,439	22,390	12,068

Notes: This table presents the average marginal effect (AME) of time spent in the lead on the likelihood of exiting the auction marketplace for our sample of bidders who lose to a BIN event. Specifications (2)-(6) introduce an extensive, nested set of controls. See text for details and discussion.

bidder will return to the site. We isolate this variation by introducing a large set of controls for the former source: the timing and the level of the standing high bid as well as attributes of the standing high bidder. This is our identification assumption—that conditional on this large set of controls, the timing of the arrival of the BIN event is exogenous. In Appendix A.2 we show the robustness of our results to omitted variables bias following the suggestions of Altonji et al. (2005) and Oster (2019). We show that one would need to hold very particular beliefs about the covariance structure of the observables and unobservable confounds in order to qualitatively overturn our result. This is a particularly apt test here because of the combination of a rich set of controls and the apparent insensitivity of our estimates to those controls.

Table 1 shows the average marginal effects (AMEs) on exit from spending an additional 24 hours in the lead, using six probit specifications. The first column presents the slope of Figure 1, with time rescaled to be in days rather than hours. The estimated marginal effect of an additional day in the lead is 7.3 percentage points over the baseline of 28%. That corresponds to a 26% increase in exit.

Our first robustness check is shown in Column 2, where we control for the number of spells as the high bidder that our loser experienced in the course of the auction, as well as the decile of the ratio of the losing bid to the BIN price. These covariates are proxies for bidder attentiveness and willingness to pay. A bidder who has high willingness to pay may be more or less likely to exit because the high willingness to pay reflects limited options in other auctions, fixed price listings, or non-eBay merchants. Her high bid is unlikely to be reached by other bidders, giving her a long spell as the winner. The mirror image of this is a "bargain hunter" who enters the auction at the very beginning with a low bid hoping to get lucky. We expect that bidder to enjoy a long spell as the top bidder since most bidding happens at the very end. This happens in part because the search ranking algorithm promotes auctions ending soon, a preference perhaps shared by eBay bidders. The estimated marginal effect falls only slightly to 6.9 percentage points with these added controls.

In Column 3 of Table 1 we add variables that characterize the auction and the seller to absorb some of the variation in exit rates. We use the product category of the item, the intended duration and ending day of the week for the auction, the natural log of the number of item page views for each day the listing was up, a set of dummies that describe the number of transactions that the seller had completed prior to the auction, the item condition (new, used, refurbished, unknown) and whether the item was in the product catalog (a commodity item).[20] Exit rates vary by product

20. The dummies for the number of transactions that the seller has completed are based on the following intervals: 0, $[1, 10]$, $[11, 50]$, $[51, 100]$, $[101, 1000]$, > 1000.

category, with clothes having the lowest and tickets the highest. Experienced sellers are more likely to provide better service and produce less exit from the platform, as shown in Nosko and Tadelis (2015). The duration variable is meant to capture bargain hunters, who are likely to return. The page views variable allows us to control for characteristics unobservable to the econometrician that correlate with the listing's desirability. For instance, a misspelling that makes a listing hard to find or high-quality photos, which influence search rank, would be captured by this metric. With these, the estimated effect on exit drops to 6.5 percentage points, which is still economically and statistically significant.

Column 4 of Table 1 adds a set of dummy variables corresponding to deciles of scheduled time remaining when the BIN event occurs and a set of dummies corresponding to quintiles for auction part for the first bid of the losing bidder. This addresses our concern that bidders who arrive early may be different from those who arrive late, in a way correlated with platform exit. This does not seem to be the case; the estimated effect is 6.7 percentage points.

The penultimate column adds the logged number of events and sessions between the time that our buyer appears on the site and the lost auction start time, per day. Events are actions on the site, such as a search query or a review of the bidding history of a listing. Whenever more than 30 minutes pass between events, a new session is started. Both of these variables are meant to proxy for interest in the site, because more interested users may be less likely to exit the platform. They also allow us to separate the effect of being more attentive from time in the lead. Controlling for these variables reduces the estimated effect only slightly to 6.4 percentage points.

In the final column of Table 1 we add demographics: annual household incomes of the users, their genders, and ages. These variables are missing for almost half the sample, but as they are important controls, we believe that their inclusion is a useful robustness check.[21] The estimate of the marginal effects on exit from an additional 24 hours in the lead remains steady at 6.4 percentage points.

Coefficients on the additional controls added in these specifications are reported in Appendix A.3. While many of them might be construed to proxy for reference points (*e.g.*, the timing or level of the initial bid), we do not dwell on them because they are chosen by the bidder themselves, and therefore may be endogenous to exit. Nonetheless, Table A.5 documents that bidders who submit higher bids relative to the BIN price are more likely to exit, and that there is no clear relationship between the timing of the initial bid and exit.

Figure 6 plots the expected probability of exit from the probit specification in Column 6 of Table 1 as a function of time in the lead with a 95% confidence interval. Figure 7 shows the average marginal effect on exit from an additional 24 hours in the lead from specification 6 of Table 1 as a function of time in the lead with a 95% confidence interval.

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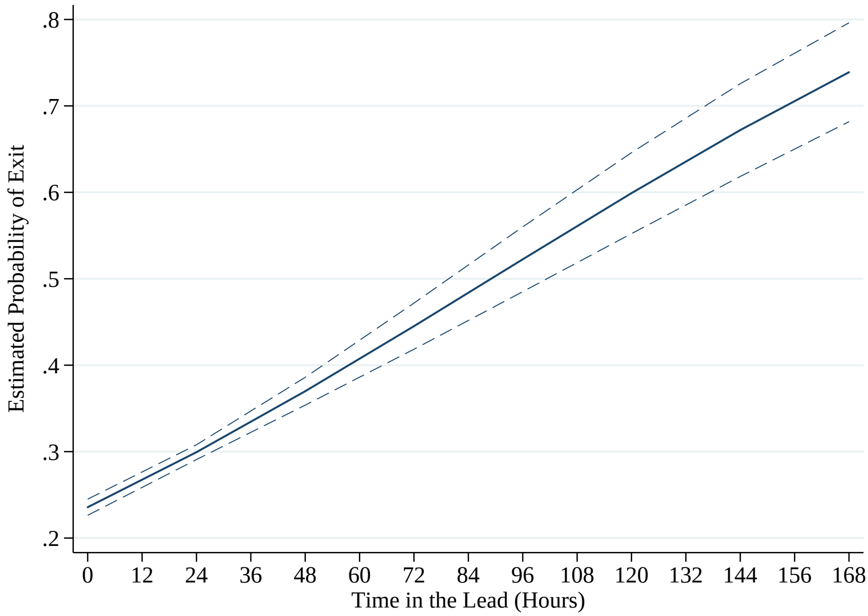
21. Age is the main variable that is missing from our data.

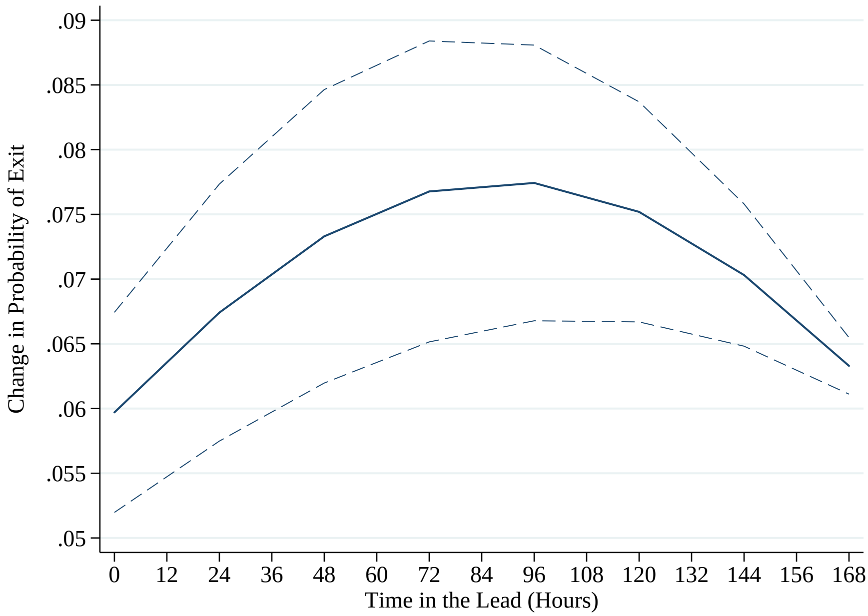
FIGURE 6. Estimated Probability of Exit by Hours in the Lead



Notes: This figure presents a plot of the predicted probability of exit as a function of time in the lead using specification (6) of Table 1.

The concave shape indicates that the marginal impact of time in the lead on exit increases with time in the lead, and drops off once someone has been winning for most of the auction, yet it is always positive, and significantly different from zero. As such, the analysis provides strong evidence, both large in magnitude and highly statistically significant, that spending more time in the lead before losing the item abruptly causes the bidder to be more likely to exit the auction platform to avoid such future experiences.

Figure 7. Marginal Effect on Probability of Exit of 24 Additional Hours in the Lead



Notes: This figure presents a plot of the average marginal effect (AME) on the predicted probability of exit as a function of time in the lead (*i.e.*, plugging in alternative values for time spent in the lead) using specification (6) of Table 1.

5.2. H2: When Loss is Expected

Hypothesis 2 is a placebo test. It claims that the exit rate of bidders who have been outbid, and therefore anticipate loss at the end of the auction, should show no sensitivity to time spent in the lead. To test this, we augment our sample with first-time bidders who lost with more than 12 hours remaining in the auction. We impose the 12-hour restriction guarantee that they had ample time to respond, *i.e.*, to exclude bidders who lose to "sniping."[22] Intuitively, they had an opportunity to counter-bid and chose not to, updated their expectations, and therefore anticipated their loss.

Table 2. AME of an Additional 24 Hours in the Lead on Exit by Loser Type

	(1) AME	(2) AME	(3) AME	(4) AME	(5) AME	(6) AME
AME:						
Binned Loser	0.076***	0.077***	0.075***	0.064***	0.060***	0.059***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Non-Sniped Loser	0.011***	0.013***	0.009***	-0.010***	-0.012***	-0.005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
Bid-Bin Ratio and Spells		Yes	Yes	Yes	Yes	Yes
Auction Attributes			Yes	Yes	Yes	Yes
Time Variables				Yes	Yes	Yes
Site Visits					Yes	Yes
Demographics						Yes
N	141,345	141,345	141,340	141,340	81,845	27,380

Notes: This table presents the average marginal effect (AME) of time spent in the lead on the likelihood of exiting the auction marketplace for bidders who lose to a BIN event as well as bidders who were outbid. Specification (2)-(6) introduce an extensive, nested set of controls. See text for details and discussion.

Table 2 recreates Table 1 for this augmented sample, where we allow for separate constant and slope index function parameters for the two sets of bidders: those who

22. The results are not sensitive to using a 6 hour or a 24 hour cutoff. The added observations come from a disjoint set of auctions from our main analysis. These are also losers, but the manner in which they were bested is different: they were outbid, rather than lost to a BIN, with some time in which to respond.

An alternative exercise would have been to look for evidence of reference point formation among sniped bidders. We considered this, end even identified such effects with sniping in unpublished, exploratory regressions for our prior work, Backus et al. (2015), however the ABIN setting has a critical advantage: the timing of the arrival of the BIN bidder generates variation in time spent in the lead that is uncorrelated with the losing bidders probability of return. In contrast, there is no such exogenous variation driving the time spent in the lead for bidders who were sniped.

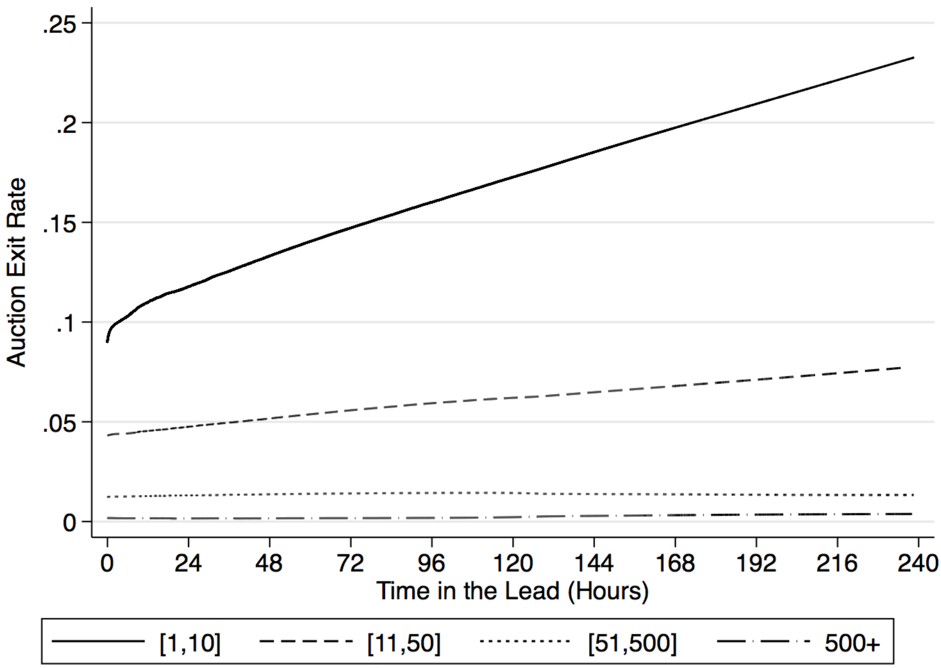
lose to a BIN, and those who are outbid. In order to make the results comparable, we exclude observations from the original sample in which the bidder lost to a BIN in the last 12 hours of the intended auction duration, but this is very rare, consistent with Figure 5a (as the standing high bid has typically exceeded 50% by then). We see substantively smaller effects for ordinary losers that are sometimes negative and sometimes positive in specifications (1)-(5). Moreover the effect is not statistically significant when we include the full set of controls in specification (6). We interpret these findings as confirmation of Hypothesis 2. These bidders share the same material outcome for their efforts, but only those for whom the loss was a surprise is time in the lead predictive of exit.

5.3. H3: Experienced Losers

Hypothesis 3 claims that more experienced bidders will be less sensitive to disappointment—and therefore time spent in the lead—when an auction is canceled, for two reasons. First, more experienced bidders are a selected sample with, in expectation, a worse outside option. Second, bidders should update their beliefs less with each additional experience.

Figure 8 recreates Figure 1 accounting for user experience. It presents LOWESS plots of exit against time in the lead for sets of bidders with different levels of experience. Consistent with Hypothesis 3, the correlation between time in the lead and exit declines markedly as users accumulate additional experience. For bidders with 51 or more prior transactions, there appears to be no effect at all. While it is true that more experienced bidders are selected to be less likely to leave the platform in general – a level effect, which we observe at the intercept with the Y axis – this fact does not explain the slope of these lines, *i.e.*, the correlation with time spent in the lead. These results are strongly consistent with Hypothesis 3, that experience on the platform dampens bidders' sensitivity to the disappointment of expectations, however we observe that they are also consistent with alternative explanations: for instance, new bidders may suffer more disappointment because they underestimate the likelihood of a BIN event, whereas experienced bidders have adjusted their expectations.

Figure 8. Exit Rates by Time in the Lead for Experienced Bidders



Notes: This figure replicates Figure 6 by plotting exit rates against time spent in the lead for four samples of bidders who lose to a BIN event: bidders with experience in 1 to 10 prior transactions, 11 to 50 prior transactions, 51 to 500 prior transactions, and 500+ prior transactions.

5.4. H4: Returning to Auctions versus Buy-It-Now Listings

Hypothesis 4 claims that, among bidders who do ultimately return to the eBay platform, time spent in the lead will be positively correlated with avoidance of the auctions. Rather, these bidders may prefer participate only on the fixed–price portion of the website, where there are fewer surprises.

For this regression we use the restricted subsample of bidders who do ultimately return to the platform in any capacity. We use the same dependent variable, exit from the auction portion of the platform, which is equal to one for 93.55% of the sample. For the remaining 6.45%, they returned to eBay but only ever participated in fixed price listings in the six months following their loss to a BIN.[23]

Results are presented in Table 3. Taking our preferred specification (6), we see that the average marginal effect of being in the lead for an additional 24 hours is a 1.6 percentage point increase in the likelihood that the bidder does not participate in auctions, conditional on returning to the platform. This is a 25% increase over the baseline of 6.45%, which confirms hypothesis.

23. We focus on avoidance of auctions broadly, rather than just ABIN auctions, for three reasons: first, the search functionality of the site does not discriminate between them, and it may not be clear to a bidder what is an ABIN auction and what is a regular auction. Second, the ABIN option disappears, and so the distinction is nontrivial. And third, there are other opportunities for disappointment in auctions generally; in particular, the possibility of being sniped.

Table 3. AME of an Additional 24 Hours in the Lead on Auction Avoidance Among Returners

	(1) AME	(2) AME	(3) AME	(4) AME	(5) AME	(6) AME
Time in the Lead (24 Hours)	0.020***	0.018***	0.014***	0.014***	0.014***	0.016***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Bid-Bin Ratio and Spells		Yes	Yes	Yes	Yes	Yes
Auction Attributes			Yes	Yes	Yes	Yes
Time Variables				Yes	Yes	Yes
Site Visits					Yes	Yes
Demographics						Yes
N	18,086	18,086	18,086	18,086	17,233	9,342

Notes: This table presents the average marginal effect (AME) of time spent in the lead on the likelihood of avoiding auction listings conditional on returning to the platform for bidders who lose to a BIN. Specifications (2)-(6) introduce an extensive, nested set of controls. See text for details and discussion.

6. Discussion

Our work is situated in a growing literature that studies the role of reference points in decision making; see DellaVigna (2009) and Barberis (2013) for recent surveys. Barberis (2013) argues that outside the areas of choice under uncertainty, namely finance and insurance, a lack of empirical analyses casts doubt on the importance of reference points, and of prospect theory more generally.

The main difficulty Barberis (2013) points to is the lack of guidance on what a gain or loss represent relative to well-understood reference points. He states that the rational expectations solution offered by Kőszegi and Rabin (2006) “remains a hypothesis in need of more testing and, in any case, is unlikely to be completely correct.” He later argues that “Reference dependence is the most basic idea in prospect theory, and if any element of the theory finds a permanent place in economic analysis, it will surely be this one.” Our analysis offers an application with rationally formed reference points that endogenously shift over time to explain observed behavior in a large market setting.

Documenting rationally formed, evolving reference points, involves two major measurement problems that have mostly confined the study of reference-dependent preferences to the lab. The first is finding a reference point shifter. In our setting, this is time spent as the leading bidder, which is consistent with rational expectations reference point formation in the spirit of Kőszegi and Rabin (2006). The data confirm that the longer a bidder holds the high bid, the more likely it is that she will win the auction. This parallels the reference point shifter in Card and Dahl (2011), who exploit the fact that rational expectations about NFL game outcomes can be measured using betting markets. The second problem is finding a measure of *ex post* disappointment when the BIN option is exercised. Platform exit serves this purpose in our study, and it is also economically important. We believe that this is the clearest example of reference-dependent preferences using observational data from real market behavior to date. Card and Dahl (2011) use family violence as the outcome variable and find that upset losses strongly impact family violence, while losses in games that were expected to be close have small and insignificant effects. Hence, both studies provide confirmation of rational reference point formation.

Even though Card and Dahl (2011) is the closest study to ours in many respects, we do find an interesting difference between the exit behavior of individuals in our marketplace and the violent behavior in their setting. NFL football games last for several hours, creating the opportunity for updating the reference point during the game. Card and Dahl (2011) test for such updating using the score at halftime and conclude that behavior is driven by the game outcome relative to expectations *at the start of the game*, with no updating of reference points based on halftime information. We find that individuals appear to update their reference points in two important ways. First, time in the lead seems to rationally shift their beliefs about the likelihood of winning the object. Second, and more striking, if they lose and have recourse to re-bid, and choose not to, then they update their reference point in an extreme way. Namely, their behavior suggests that they seem to shed the expectation of winning the auction, regardless of how long they were in the lead beforehand.

There are at least two candidate explanations for why belief updating seems to occur in our setting but not in that of Card and Dahl (2011). First, most auctions last for several days, whereas a football game lasts for just over three hours. It is plausible that the short time is not enough for viewers to update the beliefs they had just 90 minutes before halftime. Second, it is common for sports viewers to consume alcohol while viewing a game.[24] Hence, the ability of such intoxicated viewers to update their beliefs and calm down when the halftime score suggests a high likelihood of their team losing, may be a Herculean task indeed.

Our study points at the potential for future empirical work in identifying the magnitude and significance of behavioral biases using data from the exponentially

24. As noted in Niall McCarthy's article titled "Alcohol & Sport: A Match Made In Heaven?" (*Forbes Magazine*, 10/27/2016), "American football is the premier U.S. sport for drinking with 84% consuming alcohol while watching it on television."

growing datasets associated with online consumer behavior. As ours and other recent studies demonstrate, the breadth and increasing availability of online market data promises new directions for testing behavioral theories and developing an empirical behavioral research agenda that reaches far beyond lab environments. Moreover, it points to reciprocal opportunities for behavioral economics to benefit the design of online markets. Here we have highlighted one way for the design of a selling mechanism to drive buyer exit via disappointment, however, ABIN auctions are not the only suspect case. Other examples include sniping in fixed ending-time auctions, studied by Roth and Ockenfels (2002) and Backus et al. (2015); deviations from promised delivery times—encouraging sellers to promise faster ship times may increase sales, but also disappointment when those promises are not met—and, in similar spirit, arrival time estimates in ride-hailing apps. In these examples and many more, we believe there are unrealized gains from balancing tradeoffs between market design and behavioral economics.

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Appendix: Empirical Appendix

Tables A.1 and A.2 below display summary statistics for our sample.

We conducted a series of robustness checks out of concern both for the exogeneity of our variation as well as the interpretation of the effects. First, we use a linear probability model with a heteroskedasticity-robust variance-covariance matrix in Appendix Section A.1. This is partly a specification check and partly meant to lay the ground for our second check, that applies Altonji et al. (2005) and Oster (2019) to calculate bounds on the omitted variable bias under proportional selection on observables and unobservables.

This robustness exercise, reported in Section A.2 relies on adding control variables which have substantial explanatory power on the outcome. To that end, we collected extensive controls on the timing and levels of bids, demographic characteristics of bidders based on internal proprietary data, as well as the characteristics of the auction and the seller.

Finally, we also include, in Section A.3, additional results for various alternative specifications of the model.

A.1. Linear Probability Model

As a specification check and prelude to Section A.2, we replicate our results using a linear probability model (LPM) rather than the probit approach of Section 5 LPM estimates are reported in Table A.3. They are somewhat larger than the probit AMEs, but they have a very similar pattern of adjustment to covariates.

Table A.1. Summary Statistics: Auctions and Bids

	Mean	Std. Dev	Min	Max	N
Abandoned Auctions After Losing	0.28	0.45	0	1	23,439
Abandoned eBay After Losing	0.23	0.42	0	1	23,439
Number of Distinct-Auction Bids In the Year Since Losing	20.1	116.99	0	8770	23,439
Number of BINs In the Year Since Losing	3.15	10.32	0	367	23,439
Perc. Diff. B/W Subseqent Attempt and Losing Bid	1764.1	29300.02	-99.9	999900	2,093
Attempted to Buy Same Product ID	0.29	0.45	0	1	7,294
Time in the Lead (24 Hours)	0.61	0.91	0.000012	9.42	23,439
Time in the Lead Intervals	1.13	0.49	1	11	23,439
Losing Bid-BIN Price Ratio	34.6	20.13	0.0024	100.0	23,439
Seller's Previous Transaction Count (1Ks)	32.9	276.16	0	4183.5	23,439
Item Page Views Per Day Up	105.7	329.22	0.29	18078.3	23,439
Events Before Auction Was Up (Normalized)	176.2	11146.98	0.00010	1589760	22,390
Sessions Before Auction Was Up (Normalized)	2.04	69.76	0.00010	8640	22,390
Item in Product Catalog	0.31	0.46	0	1	23,439
Listings Within 1 Year for Losing Product ID	2541.2	9209.17	1	154947	7,294
First Bid Normalized By Duration	0.26	0.27	0.00014	1.00	23,439
Scheduled Time Remaining When Outbid (Hours)	95.7	54.38	0.0011	240.0	23,439
Intended Lost Auction Duration (Days)	5.52	2.22	1	10	23,439
Intended Auction End Day:					
Sun	0.15	0.35	0	1	23,439
Mon	0.15	0.36	0	1	23,439
Tue	0.15	0.36	0	1	23,439
Wed	0.15	0.36	0	1	23,439
Thu	0.14	0.35	0	1	23,439
Fri	0.13	0.34	0	1	23,439
Sat	0.13	0.33	0	1	23,439
Vertical:					
Clothes	0.46	0.50	0	1	23,439
Phones	0.46	0.50	0	1	23,439
Auto Parts	0.063	0.24	0	1	23,439
Tickets	0.022	0.15	0	1	23,439
Item Condition:					
New	0.42	0.49	0	1	23,439
Refurbished	0.017	0.13	0	1	23,439
Used	0.53	0.50	0	1	23,439
Unknown	0.032	0.18	0	1	23,439

Notes: This table presents summary statistics concerning auction and bid attributes from our main dataset of first-time bidders who participate in ABIN auctions and ultimately lose. See the text for further details on sample definition.

A.2. LPM Coefficient Stability

While our coefficients are stable as we add covariates, that is not a sufficient condition for omitted variable bias to be negligible. Figures A.1 and A.2 are based on the omitted variable bias bounding approach of Oster (2019). We assume that the unobservables share at least some of the covariance properties of the observables

Table A.2. Summary Statistics: Bidders

	Mean	Std. Dev	Min	Max	N
Female User	0.62	0.49	0	1	18,836
User Age (2 Year Increments)	35.0	14.42	18	99	13,650
Annual Household Income:					
<15K	0.15	0.35	0	1	23,316
15-19K	0.066	0.25	0	1	23,316
20-29K	0.12	0.33	0	1	23,316
30-39K	0.11	0.32	0	1	23,316
40-49K	0.098	0.30	0	1	23,316
50-74K	0.21	0.40	0	1	23,316
75-99K	0.10	0.31	0	1	23,316
100-124K	0.055	0.23	0	1	23,316
125K+	0.086	0.28	0	1	23,316

Notes: This table presents summary statistics concerning bidder attributes from our main dataset of first-time bidders who participate in ABIN auctions and ultimately lose. See the text for further details on sample definition.

Table A.3. LPM Marginal Effect of an Additional 24 Hours in the Lead on Exit

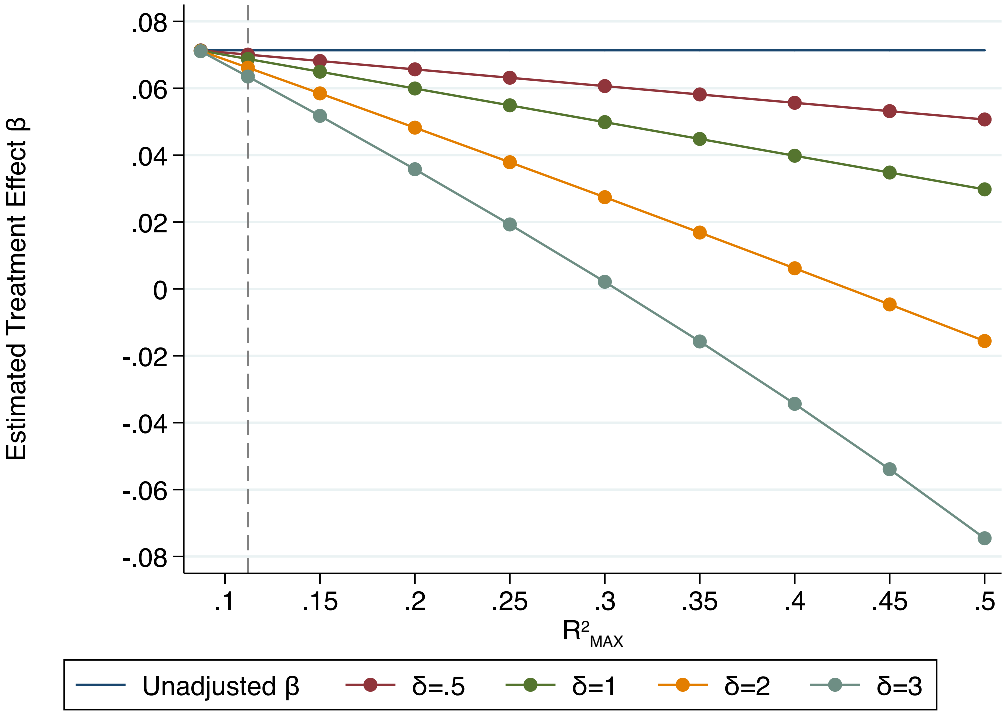
	(1) ME	(2) ME	(3) ME	(4) ME	(5) ME	(6) ME
Time in the Lead (24 Hours)	0.080***	0.076***	0.073***	0.075***	0.072***	0.071***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Bid-Bin Ratio and Spells		Yes	Yes	Yes	Yes	Yes
Auction Attributes			Yes	Yes	Yes	Yes
Time Remaining				Yes	Yes	Yes
Site Visits					Yes	Yes
Demographics						Yes
N	23,439	23,439	23,439	23,439	22,390	12,068
R^2	0.03	0.04	0.05	0.05	0.08	0.09

Notes: This table presents the LPM analogue of the profit specification employed in Table 2. As before, specifications (1)-(6) introduce extensive nested set of controls.

we selected. Without this reasonable assumption, very little can be said about the merits of our identification strategy.

The horizontal line in Figure A.1 shows the marginal effect on exit from an additional 24 hours in the lead from specification (6) in Table A.3. The bias of this estimate depends on two unknown in-sample parameters: the R^2 from a hypothetical regression of the outcome on all observed and unobserved determinants of exit, R^2_{MAX}, and the coefficient of selection proportionality δ. A δ of one indicates that the observed and unobserved variables have an equally important effect on the

Figure A.1. Treatment Effect Under Assumptions About Selection Proportionality



Notes: This figure presents the treatment effect for the LPM results of specification (6) adjusted according to the method of Oster (2019). See text for a discussion of this method and definition of parameters δ and R^2_{MAX}. The dashed vertical line refers to the recommended value for comparison of $1.3 \cdot \tilde{R}^2$.

coefficient of interest. A δ greater than one indicates that the unobserved variables are relatively more important.[25] Similarly, an R^2_{MAX} of 1 would indicate that the *potential*

25. To fix the idea, consider our model

$$y = \alpha + \beta \cdot t + \Sigma_{j=1}^{C} \gamma_j \cdot x_j + \Sigma_{k=1}^{U} \eta_k \cdot z_k + \varepsilon = \alpha + \beta \cdot t + C + U + \varepsilon,$$

where y is the binary exit outcome, t is time in the lead, x_j are the controls and z_k are the unobserved variables. We assume that U and C are orthogonal. The proportionality of selection explanatory variables are highly predictive and there is very little measurement error or idiosyncratic variation driving a bidder's exit decision.

The green line shows the bias-adjusted marginal effect for the equal selection case ($\delta = 1$) for a range of plausible R^2_{MAX} values. Other downward-sloping lines make different assumptions about the selection proportionality. In a setting where the observed and unobserved variables explain a lot of the variation, the bias-adjusted effect turns negative. However, near the $1.3 \cdot \tilde{R}^2$ cutoff for R^2_{MAX} suggested by Oster (2019), the bias-adjusted estimates are generally near the unadjusted one and considerably above zero.[26] This suggests that our estimated effect is robust and economically significant.

For each value of R^2_{MAX}, we also calculate the value of δ that would explain away the marginal effect and reduce it all the way to zero. That value is plotted

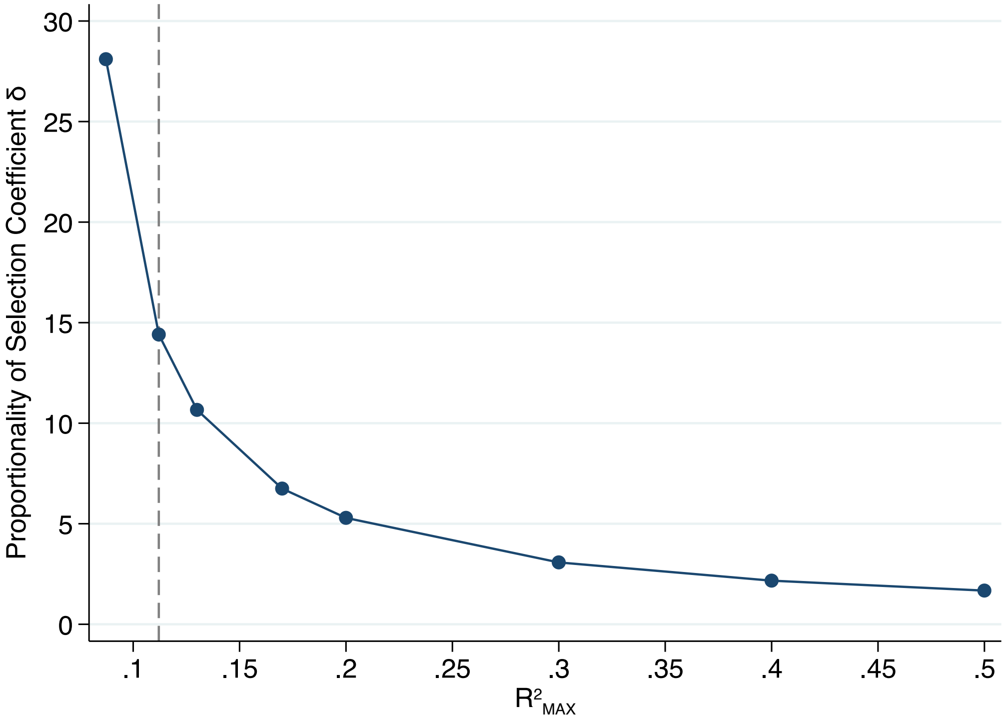
relationship is defined as

$$\delta = \frac{\frac{Cov(U,t)}{Var(U)}}{\frac{Cov(C,t)}{Var(C)}}.$$

Essentially, δ is the ratio of univariate regression coefficients of the linear index t on U and the linear index t on C. R^2_{MAX} comes from the infeasible regression of y on t and the variables that comprise C and U.

26. The cutoff is based on a sample of high-quality randomized studies that considered the sensitivity of treatment effects to the inclusion of controls. The assumption is that since treatment is experimental, these estimates should generally "survive" the adjustments process. The cutoff of $1.3 \cdot \tilde{R}^2$, where $\tilde{R}^2$ is the R^2 from the regression with the controls, allows 90% of estimates to survive. This value corresponds to a bound on δ where the unobservables explain somewhat less than the observables.

Figure A.2. Proportionality of Selection Coefficient δ s.t. $\hat{\beta} = 0$



Notes: This figure plots the proportionality of selection coefficient (δ) required to generate adjusted estimates such that $\hat{\beta} = 0$, as a function of R^2_{MAX}. We view this as a bound on the assumptions on unobserved heterogeneity required to qualitatively overturn our result. The dashed vertical line refers to the recommended value for comparison of $1.3 \cdot \tilde{R}^2$ from Oster (2019).

in Figure A.2. Near our cutoff, the unobserved variables needs to be more than 15 times as important as observed ones to completely suppress the estimated effect. When the exit decision is more predictable, at least hypothetically, a smaller role for unobservables is sufficient to reduce the estimates below zero.

Another motivation for this robustness check is that it is possible for the perceived time in the lead to exceed the measured time since users are typically not monitoring the site closely and are inattentive to outbid notifications. We use the timestamp of when the BIN event occurs to define time in the lead, but some amount of time may pass before the losing bidder reads the e-mail or becomes cognizant of in-app notification, which are instantaneous. This gap between measured time in the lead and perceived time in the lead for the user means the effect we seek to estimate will be attenuated. Since this issue can be re-expressed as a kind of omitted variable problem, this bounding approach allows us to characterize the magnitude of this measurement error-induced bias in the behavioral response.

A.3. Additional Results

Here we offer additionally, supplementary results. Table A.4 recreates the six specifications from Table 1 (by row) to consider an alternative definition of platform exit. Note that each cell of the table presents an average marginal effect for a separate regression. The first column of Table A.4 reproduces Table 1 to facilitate comparisons. The second column takes as a dependent variable exit from eBay.com altogether, not merely the auction part of the market.[27] Not surprisingly, the effect of time in the lead is somewhat weaker since some of the people who abandon auctions may substitute towards fixed price listings.

Next, Figure A.3 re-creates Figure 3 allowing the time in the lead and the auction time elapsed when taking the lead to vary independently. The variation we exploit for our main specification corresponds to conditioning on the latter (*i.e.*, fixing a point on the horizontal axis), and moving the former (*i.e.*, moving up and down the vertical

27. Einav et al. (2018) show that fixed price sales are a large and growing portion of the website, and so it is important to consider substitution to fixed-price sales.

axis). Consistent with our Assumption we see that, in the conditional variation as well, spending more time in the lead is positively correlated with a higher probability of being the ultimate winner.

Table A.5 re–visits Table 1 but includes all coefficient values from those regressions. There are many suggestive results here: for instance, the level of the losing bid relative to the BIN price appears to be correlated with the probability of exit. On the one hand this may reflect additional consequences of expectation–dependent preferences. On the other, since the bid is chosen by the bidder, it may be endogenous to the bidder's decision to return to the platform. What is unique about the variation we exploit in the main results is that it is plausibly exogenous — that variation in time in the lead, conditional on the time at which the bid is placed, is determined by the arrival time of the competing bidder, rather than any choice of the bidder of interest.

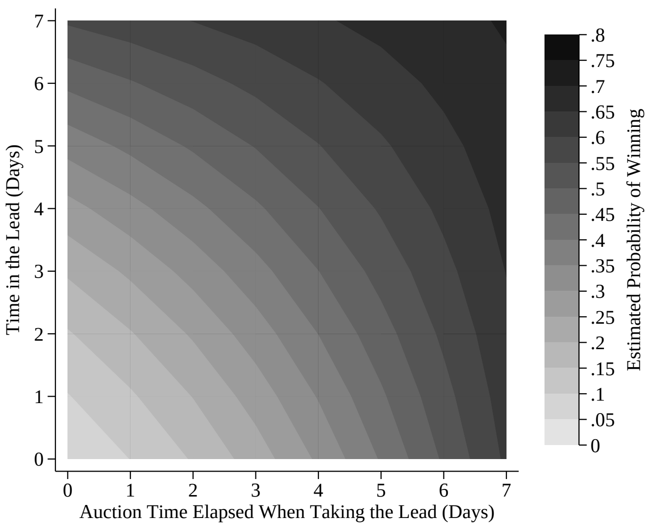
Finally, Figure A.4 recreates Figure 8 but using a specification that is linear in prior experience so that we can add confidence intervals. This allows us to confirm that, at every level of experience, the predicted exit rates as a function of experience are statistically distinct.

TABLE A.4. AME of an Additional 24 Hours in the Lead on Platform Exit

	(1) Auct. Exit	(2) eBay Exit
Spec. (1)	0.073***	0.060***
	(0.003)	(0.003)
Spec. (2)	0.069***	0.057***
	(0.003)	(0.003)
Spec. (3)	0.065***	0.056***
	(0.003)	(0.003)
Spec. (4)	0.066***	0.058***
	(0.003)	(0.003)
Spec. (5)	0.065***	0.056***
	(0.003)	(0.003)
Spec. (6)	0.063***	0.054***
	(0.004)	(0.004)

Notes: This table presents the average marginal effect (AME) of time spent in the lead on other outcomes for our sample of bidders who lose to a BIN event. Each cell of the table corresponds to a separate regression. Column-wise, we consider alternative dependent variables. See text for further discussion. Row-wise, specifications (1)-(6) correspond to the nested control sets introduced in Table 1, where Specification 6 includes observables capturing bid and auction attributes, time variables, behavioral variables, and bidder demographics.

FIGURE A.3. Probability of Winning, Two Dimensions



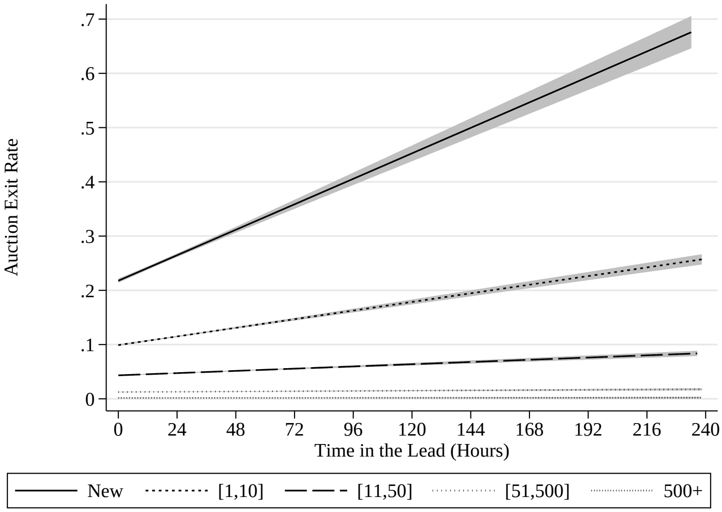
Notes: This figure presents the empirical likelihood that the bidder ultimately wins the auction, as a function of both the time spent in the lead (in days), and the auction time elapsed when they first submitted their bid. We use all auctions in the four ABIN categories during our sample period.

Table A.5. Additional Coefficient Values from Table 1

	(1) AME	(2) AME	(3) AME	(4) AME	(5) AME	(6) AME	(7) AME
Time in the Lead (24 Hours)	0.073***	0.069***	0.065***	0.066***	0.065***	0.063***	0.063***
Time in the Lead Intervals (Count)		-0.074***	-0.070***	-0.070***	-0.066***	-0.058***	-0.057***
Losing Bid/BIN Decile=2		0.023	0.027*	0.027*	0.021	0.012	0.013
Losing Bid/BIN Decile=3		0.029*	0.034**	0.032**	0.024	0.012	0.013
Losing Bid/BIN Decile=4		0.068***	0.073***	0.071***	0.060***	0.054**	0.055**
Losing Bid/BIN Decile=5		0.066***	0.070***	0.067***	0.052***	0.035	0.036
Losing Bid/BIN Decile=6		0.089***	0.095***	0.092***	0.079***	0.052**	0.053**
Losing Bid/BIN Decile=7		0.073***	0.080***	0.076***	0.063***	0.039*	0.040*
Losing Bid/BIN Decile=8		0.099***	0.103***	0.099***	0.082***	0.064***	0.065***
Losing Bid/BIN Decile=9		0.106***	0.114***	0.110***	0.091***	0.075***	0.076***
Losing Bid/BIN Decile=10		0.120***	0.124***	0.120***	0.106***	0.073***	0.074***
Vertical (Relative to Auto Parts):							
Clothes			-0.061***	-0.062***	-0.065***	-0.087***	-0.087***
Phones			0.005	0.006	-0.008	-0.040*	-0.040*
Tickets			0.013	0.017	-0.005	-0.052	-0.051
Intended Lost Auction Duration (Days)=1			-0.045***	-0.040***	-0.030*	-0.018	-0.018
Intended Lost Auction Duration (Days)=3			-0.019*	-0.014	-0.012	0.001	0.001
Intended Lost Auction Duration (Days)=5			-0.004	-0.002	-0.002	0.009	0.009
Intended Lost Auction Duration (Days)=10			-0.001	-0.006	-0.000	0.004	0.004
Scheduled End DOW (Relative to Sunday):							
Mon			0.001	0.001	0.003	0.007	0.007
Tue			-0.004	-0.003	0.003	0.004	0.004
Wed			0.002	0.003	0.005	0.011	0.011
Thu			0.005	0.005	0.008	0.004	0.004
Fri			-0.012	-0.012	-0.007	-0.001	-0.000
Sat			-0.008	-0.008	-0.006	-0.006	-0.006
Seller Experience (Relative to 0 Previous Transactions):							
$[1, 10]$			-0.007	-0.007	-0.013	-0.001	-0.001
$[11, 50]$			-0.022	-0.023	-0.032**	-0.023	-0.023
$[51, 100]$			-0.028*	-0.028*	-0.036*	-0.028	-0.028
$[101, 1000]$			-0.012	-0.012	-0.020	-0.015	-0.015
1000+			-0.043***	-0.043***	-0.052***	-0.049**	-0.048**
Log of Item Page Views Per Day Up			-0.008**	-0.004	-0.002	-0.002	-0.002
Item Condition (Relative to New):							
Refurbished			0.006	0.006	0.003	-0.001	-0.001
Used			-0.011	-0.012	-0.014*	-0.022*	-0.023*
Unknown			0.072*	0.069*	0.062*	0.076	0.075
Item in Product Catalog=1			0.004	0.003	0.002	0.016	0.016
First Bid Timing (Relative to Day One):							
First Bid Timing (Days Since Start of Auction)=2				0.010	0.001	-0.009	-0.008
First Bid Timing (Days Since Start of Auction)=3				0.021	0.014	0.015	0.016
First Bid Timing (Days Since Start of Auction)=4				0.042**	0.028*	0.019	0.020
First Bid Timing (Days Since Start of Auction)=5				0.019	0.006	0.011	0.012
First Bid Timing (Days Since Start of Auction)=6				0.038*	0.022	-0.002	-0.001
First Bid Timing (Days Since Start of Auction)=7				0.021	-0.000	0.006	0.007
First Bid Timing (Days Since Start of Auction)=8				0.111	0.098	0.178	0.180
First Bid Timing (Days Since Start of Auction)=9				0.067	0.028	0.039	0.041
First Bid Timing (Days Since Start of Auction)=10				-0.022	-0.043	-0.140	-0.138
Log of Events Before Auction Was Up (Normalized)					-0.038***	-0.038***	-0.038***
Log of Sessions Before Auction Was Up (Normalized)					0.029***	0.026***	0.026***
Annual Income for the HH (Relative to 50-74K):							
<15K						0.011	0.011
15-19K						0.005	0.005
20-29K						0.005	0.005
30-39K						-0.005	-0.005
40-49K						-0.019	-0.019
75-99K						-0.001	-0.001
100-124K						0.011	0.011
125K+						0.028	0.028
Female						0.013	0.013
User Age (2 Year Increments)						0.001***	0.001***
Number of Bidders in Lost Auction							-0.001
N	23,439	23,439	23,439	23,439	22,390	12,068	12,068

Notes: This Table presents the omitted coefficient values from Table 1. See notes from that table and discussion in text for details on the models.

FIGURE A.4. Exit Rates by Time in the Lead for Experienced Bidders—Linear Fit, Confidence Intervals



Notes: This figure replicates 6 by plotting exit rates against time spent in the lead for four samples of bidders who lose to a BIN event: bidders with experience in 1 to 10 prior transactions, 11 to 50 prior transactions, 51 to 500 prior transactions, and 500+ prior transactions. Unlike the fit in Figure 8, here we impose linearity in experience and plot confidence intervals on the predicted rates.