RESEARCH ARTICLE | PSYCHOLOGICAL AND COGNITIVE SCIENCES

Understanding the first-offer conundrum: How buyer offers impact sale price and impasse risk in 26 million eBay negotiations

Martin Schweinsberg[a,1,2], Hannes M. Petrowsky[b,1,2], Burkhardt Funk[c], and David D. Loschelder[b]

Edited by Timothy Wilson, University of Virginia, Charlottesville, VA; received November 15, 2022; accepted June 2, 2023

How low is the ideal first offer? Prior to any negotiation, decision-makers must balance a crucial tradeoff between two opposing effects. While lower first offers benefit buyers by anchoring the price in their favor, an overly ambitious offer increases the impasse risk, thus potentially precluding an agreement altogether. Past research with simulated laboratory or classroom exercises has demonstrated either a first offer's anchoring benefits *or* its impasse risk detriments, while largely ignoring the other effect. In short, there is no empirical answer to the conundrum of how low an ideal first offer should be. Our results from over 26 million incentivized real-world negotiations on eBay document (a) a linear anchoring effect of buyer offers on sales price, (b) a nonlinear, quartic effect on impasse risk, and (c) specific offer values with particularly low impasse risks but high anchoring benefits. Integrating these findings suggests that the ideal buyer offer lies at 80% of the seller's list price across all products—although this value ranges from 33% to 95% depending on the type of product, demand, and buyers' weighting of price versus impasse risk. We empirically amend the well-known midpoint bias, the assumption that buyer and seller eventually meet in the middle of their opening offers, and find evidence for a "buyer bias." Product demand moderates the (non)linear effects, the ideal buyer offer, and the buyer bias. Finally, we apply machine learning analyses to predict impasses and present a website with customizable first-offer advice configured to different products, prices, and buyers' risk preferences.

negotiation | first offer | impasses | anchoring | machine learning

Significance

Negotiations are omnipresent. People negotiate salaries, the price of a house, car, or anything for sale at an antique store, bazaar, or online marketplace. In price negotiations, a vexing question plagues buyers everywhere. How ambitious is the ideal first offer? While more ambitious offers lower the price, they also risk nonagreement. The literatures in psychology, management, and data science have yet to offer an empirical answer to this first-offer conundrum. Based on over 26 million eBay negotiations, we generate an answer that integrates a linear anchoring effect on price and nonlinear effects on impasse risk. We offer applied, machine learning–based recommendations and contribute to the scholarly debate by establishing first-offer effects and nonlinear relationships that are incompatible with current theorizing.

Your first offer should be just this side of crazy, as opposed to that side of crazy.
(Galinsky & Schweitzer, 2015)

Negotiators everywhere have to decide. How ambitious should my first offer be? The first-offer conundrum is identifying "this side of crazy" versus "that side of crazy" (see ref. 1, p. 252). On the one hand, many studies (2, 3) show that ambitious first offers help negotiators claim value as they favorably anchor the counterpart (e.g., refs. 2, 4–7), thus causing lower final prices for buyers or higher final prices for sellers. First offers anchor negotiations by making anchor-consistent information selectively accessible (5, 8), or by causing recipients to insufficiently adjust their counteroffers away from the anchor (9–12). On the other hand, some studies (fewer than 15, see refs. 13 and 14) have shown an opposing effect. Ambitious offers can increase the risk of impasses, i.e., no deal whatsoever (13, 15–17). Overly ambitious first offers on "that side of crazy" upset the counterpart [(18), chapter 9], destroy trust (19), violate "appropriate" negotiation behavior (20), and cause offense, thus increasing the impasse risk (15).

To understand this first-offer conundrum, we first reviewed negotiation guidebooks and peer-reviewed articles,* consulted 35 expert negotiation scholars with an average of 12.88 years of experience (*SD* = 7.98), and searched the literature for advice from practicing professionals. Strong consensus emerged that negotiators should "open ambitiously, but not *too* ambitiously" (*SI Appendix*, Table S1). However, the line between "this and that side of crazy" continues to remain largely unclear. When is a first offer too ambitious? The negotiation experts we asked advised buyers to make first offers ranging from 15% to 100% of the seller's list price (*M* = 59.94%), with an *SD* = 23.74%. Currently, negotiators need to rely on academic advice that is, at times, unclear and vague (*SI Appendix*, Table S1, #3, #9–11), void of empirical evidence (#1–2, #4–7, #12–13), and potentially even conflicting (#11, #14).

*To our knowledge, no peer-reviewed articles have examined or quantified how ambitious the sellers' or buyers' first offer should be for maximal negotiation success. In addition, prior research on first-offer magnitude is predominantly based on simulated lab or classroom studies with limited ecological validity (33).

Author contributions: M.S. and H.M.P. contributed equally to this project, M.S., H.M.P., B.F., and D.D.L. designed research; M.S., H.M.P., B.F., and D.D.L. performed research; H.M.P. analyzed data; and M.S., H.M.P., B.F., and D.D.L. wrote the paper.

The authors declare no competing interest.

This article is a PNAS Direct Submission.

[1]M.S. and H.M.P. contributed equally to this work.

[2]To whom correspondence may be addressed. Email: martin.schweinsberg@esmt.org or hannes.petrowsky@leuphana.de.

This article contains supporting information online at https://www.pnas.org/lookup/suppl/doi:10.1073/pnas.2218582120/-/DCSupplemental.

Published August 1, 2023.

From a theoretical perspective, prior studies have yet to provide empirical evidence for two prominent but untested assumptions of linearity. We do not yet know whether increasingly ambitious first offers (a) exert a linearly more potent anchoring effect, and (b) are related linearly to a higher risk of impasse. Prior studies, however, are predominantly based on assumed linearity (21). Theorizing suggests that higher anchors coincide with particularly insufficient adjustment (e.g., ref. 22), with more selectively accessible anchor-consistent knowledge (e.g., ref. 23), and with more assertive offers being perceived as more obnoxious and aggressive (e.g., ref. 14). Our sample of negotiation experts also strongly agreed with this notion of linearity (M = 5.34; SD = 1.53; t[34] = 5.18, P < .001, d = 0.88).

The literature, however, has yet to empirically test either of these linearity assumptions in a sufficiently fine-grained way. This seems particularly crucial as related findings suggest potential nonlinearity: In economic games, participants reject seemingly unfair offers in a nonlinear fashion if these offers are just below a perceived meaningful standard (20). Nonlinear relationships also emerged between negotiators' alternatives and first-offer magnitude (24), as well as between first-offer precision and anchor potency (25). Negotiators' psychological reactions to increasingly ambitious offers could plausibly be nonlinear as well (26). For instance, anchoring effects could level off at a certain point (27) and asymptotically reach a maximal effect (28). Alternatively, the impasse risk might only begin to increase once a certain threshold of first-offer ambition is crossed; in turn, it might level off after surpassing a certain level of excessive ambition. These forms of nonlinearity would expand our theoretical understanding of first-offer effects as much as help negotiators craft optimized offers that maximize value *and* minimize impasse risks.

Finally, our research empirically tests the popular notion of midpoint bias, which posits that negotiators (buyer and seller) are likely to agree on a final price close to the midpoint of their opening offers (1, 18, chapters 4 and 9). Despite the bias's prominence among scholars and practitioners, prior research has yet to empirically confirm this assumption. In contrast, prior research has also found evidence that buyers can systematically outperform sellers in symmetrical, competitive market simulations—suggesting a buyer bias (e.g., refs. 29 and 30). Examining the first-offer conundrum, linearity assumptions, and opening-offer midpoint bias requires enormous datasets with continuous variation in offer magnitude, ideally with real-world incentives (31, 32), as well as information on both negotiators' opening offers, the final prices, and the overall impasse likelihood.

The present research explores the first-offer conundrum by integrating the distinct research lines and the competing effects observed for first-offer anchoring and impasses. We empirically examine untested theoretical assumptions of linearity and the midpoint bias with 26,454,176 incentivized, real-world negotiations on eBay (33–35). To our knowledge, this is the first large-scale test of first offers' impasse and anchoring effects. We quantify when the anchoring benefits of buyers' offers outweigh the elevated impasse risk, examine moderation by buyers' product demand, create machine learning–based classification models for predicting deals versus impasses, and translate the findings into applied first-offer recommendations [https://www.firstofferadvice.com; (36)].

Results

Linear Anchoring Effects of Buyers' First Offers on Final Prices. As Fig. 1 illustrates, regressing final sales prices on buyers' first-offer magnitude showed a fully linear anchoring effect. Lower (more ambitious) buyer offers (in % of sellers' list price) coincided with lower final sales prices, provided negotiations did not end with an impasse. The linear regression showed an extensive fit of R^2 = .997,

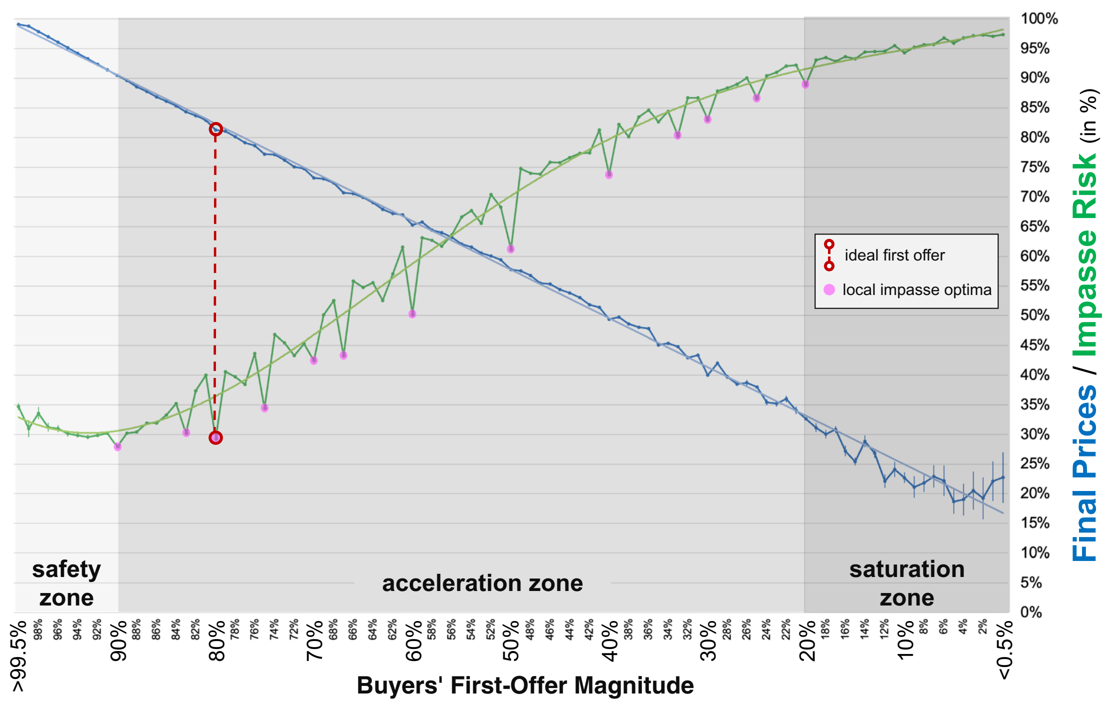

Fig. 1. (Non)Linear effects on final sales price and impasse risk. Note. Buyers' first-offer magnitude (100% to 0%, in steps of 1%) exerts a linear effect on final sales prices (blue) and a nonlinear, quartic effect (fourth-order polynomial) on impasse risks (green). An integrative, joint perspective of both effects establishes the ideal first offer at 80% (marked in red) because the combination of green (impasse risk) and blue (final price) datapoints are lower than for any other combination of datapoints. When solely focused on impasses, the lowest risk occurred for 90% offers. Local impasse optima (n = 13, marked in magenta) are significant drops below the quartic function. Error bars constitute 99% CIs. The CIs are, at times, very short and barely visible.

b = 0.82, F(1,99) = 35,627.82 (*SI Appendix*, Table S4*A*). Adding higher order polynomials (i.e., quadratic, cubic) did not increase model fit (ΔR^2 = .000) and did not result in significant model improvements (P > .968), suggesting a fully linear anchoring effect of buyers' first offers[†] (Fig. 1; blue line).

Nonlinear Effects of Buyers' First Offers on Impasse Risk. For impasse risk, our analyses established nonlinear effects (Fig. 1, green line). A linear regression with buyers' first-offer magnitude as predictor and the continuous impasse risk as the criterion resulted in a fit of R^2 = .959—more ambitious offers coincided with a higher impasse risk (AIC = 611.72, BIC = 616.95). However, this strictly linear model does not capture any of the nonlinear aspects evident in Fig. 1. The best model fit emerged for a *quartic* model, R^2 = .988, AIC = 486.64, BIC = 499.72, P < .001 (i.e., including polynomials up to the fourth order; see light green function in Fig. 1; *SI Appendix*, Table S5 *A* and *B*). A subsequent locally weighted regression ("LOWESS") established three distinct zones of impasse risks. From left to right, the impasse risk first remained stable, even decreased slightly (i.e., a *safety zone* for offers >90%[‡]), then increased markedly (*acceleration zone*; 90% to 20%), until it leveled off upon having crossed a threshold of offer ambition (*saturation zone* for offers <20%).

Local Impasse Optima. Fig. 1 also reveals local impasse optima (magenta-colored dots). Specific values of buyers' first-offer magnitude coincided with a particularly low impasse risk, even significantly *below* the quartic function. Thirteen optima emerged for offers of 90%, 83% (5/6), 80%, 75%, 70%, 67% (2/3), 60%, 50%, 40%, 33% (1/3), 30%, 25%, and 20% (37). Robustness checks confirmed that these local impasse optima persisted when excluding round list prices (i.e., prices divisible by five without remainder, e.g., $100.00, $95.00), round buyer offers (also divisible by five without remainder), or both (*SI Appendix*, Fig. S1 *Q*–*S*). The local impasse optima are therefore not limited to round list prices and/or round buyer offers.

The Ideal First Offer for Buyers. Integrating these linear anchoring effects on the price and the nonlinear effects on impasse risk shows that, averaged across all 34 product categories, the ideal first offer for buyers lies at 80% of the seller's list price (Fig. 1, marked in red). This 80% offer comprises the optimum because the combination of datapoints for impasse risk *and* sales price is lower than for any other first-offer value. Importantly, however, this 80% recommendation is based on buyers weighting the importance of price and impasse risk equally. Giving relatively more priority to the price (impasse risk) shifts the ideal first offer farther right (*left*; Fig. 2). First-offer recommendations also differ across product categories and product demand, and range from 95% for "coins and paper money" to 33% for miscellaneous products that did not fit into any other category (category: "everything else"; see https://firstofferadvice.com/advice).

[†]For full transparency, the seller's first offer (i.e., list price)—chronologically, the very first offer that is being made—also linearly predicted the final price [R^2 = .945, b = 0.76, $RMSE$ = 47.44, F[1, 11,772,811] = 204,159,624.36, P < .001; (63)]. We urge readers to treat this "anchoring" effect with caution; however, as it may be (predominantly) driven by the markedly different objective values of advertised products (e.g., a pen for $2 versus a MacBook for $1,500).

[‡]An examination of the points of zero slope with the derivative of the quartic function showed that the regression function had one point of zero slope at x = 92.79%. Here, the slope changes from negative to positive (i.e., local function minimum/trough), which corroborates the "safety zone" interpretation that the impasse risk first *de*creases before it then accelerates in the acceleration zone and levels off in the saturation zone.

Impasse Risk →

Product Demand ↑ Seller's List Price: **$500**	Low Impasse Risk (< 40%)	Medium Impasse Risk (< 60%)	High Impasse Risk (< 80%)
Computers & Consumer Electronics (High Demand)	$440	$335	$250
Jewelry & Watches (Medium Demand)	$375	$300	$200
Art (Low Demand)	$300	$225	$125

Fig. 2. Offer Recommendations as a function of product demand and impasse sensitivity. Note. First-offer recommendations differ as a function of buyers' demand for the respective product (top to bottom) and as a function of negotiators' individual willingness to accept higher impasse risk (left to right). Ideal first offers vary accordingly (see www.firstofferadvice.com).

Moderation by Product Demand. We expected that product demand would moderate the linear anchoring and the nonlinear impasse effects. Indeed, as Fig. 3 shows, higher product demand coincided with an overall higher impasse risk. In addition, impasse risk accelerated (and saturated) much earlier for products with high demand (e.g., smartphones; cubic model, R^2 = .978) compared to medium (e.g., clothes; quartic, R^2 = .987), and low demand products (e.g., antiques and art; cubic, R^2 = .992), which resulted in markedly narrower safety zones (Fig. 3; $S_H < S_M < S_L$). Product demand also moderated the linear anchoring effect on sales prices. The lower the demand for a product, the steeper the linear regression slopes, suggesting stronger anchoring effects (Fig. 3, blue lines; $Zs \geq 2.11$, $Ps \leq .035$).

Midpoint Bias versus Buyer Bias of Opening Offers. We probed the data for evidence of the midpoint bias using a train-validation-test split approach, regressing final prices on sellers' and buyers' first offers. Sellers' list price alone explained R^2= .168 of the variance in final prices (b = 0.14, $RMSE$ = 32.20). Adding buyers' offer magnitude as a predictor substantially increased the explained variance to R^2= .929 ($RMSE$ = 9.39). The marked increase in predictive power (ΔR^2 = .761) and model fit ($\Delta RMSE$ = −22.81) suggests that buyers' offer magnitude is more influential than sellers' list price. Fig. 4*A* shows that for all 11.77 million negotiations with an agreement, final prices (orange line) were closer to buyers' first offers (0% on Y-axis) than to sellers' first offer (i.e., list prices, 100% on y-axis). On average, buyers conceded less from their opening offers (M = 13.56%; dark gray area) than sellers did (M = 86.44%; white area). This buyer bias was largely due to the vast majority of sellers (i.e., 78.96%) deciding to directly accept the buyer's first offer (n = 9,296,323). For only those negotiations in which sellers did not directly accept the buyer's offer but decided to make a counteroffer (n = 2,476,490; 21.04%), the buyer bias persisted but was less pronounced (Fig. 4*B*, red line), with buyers conceding M = 36.67% from their first offer (light gray area), while sellers conceded M = 63.33% from their list price (white area). In all, the present data do not support the well-known midpoint bias (blue line at 50%) but establish a buyer bias between 13.56% and 36.67% (29, 30). Product demand also moderated this buyer bias in that high demand from other interested buyers reduced the bias with buyers conceding M = 25.11% compared to medium (M = 19.78%) and low demand (M = 11.70%; *SI Appendix*, Fig. S5).

Robustness and Machine Learning Analyses. Across 88 robustness analyses, we controlled for numerous potentially confounding factors. For instance, list prices ≤ $2,500 versus > $2,500, buyers

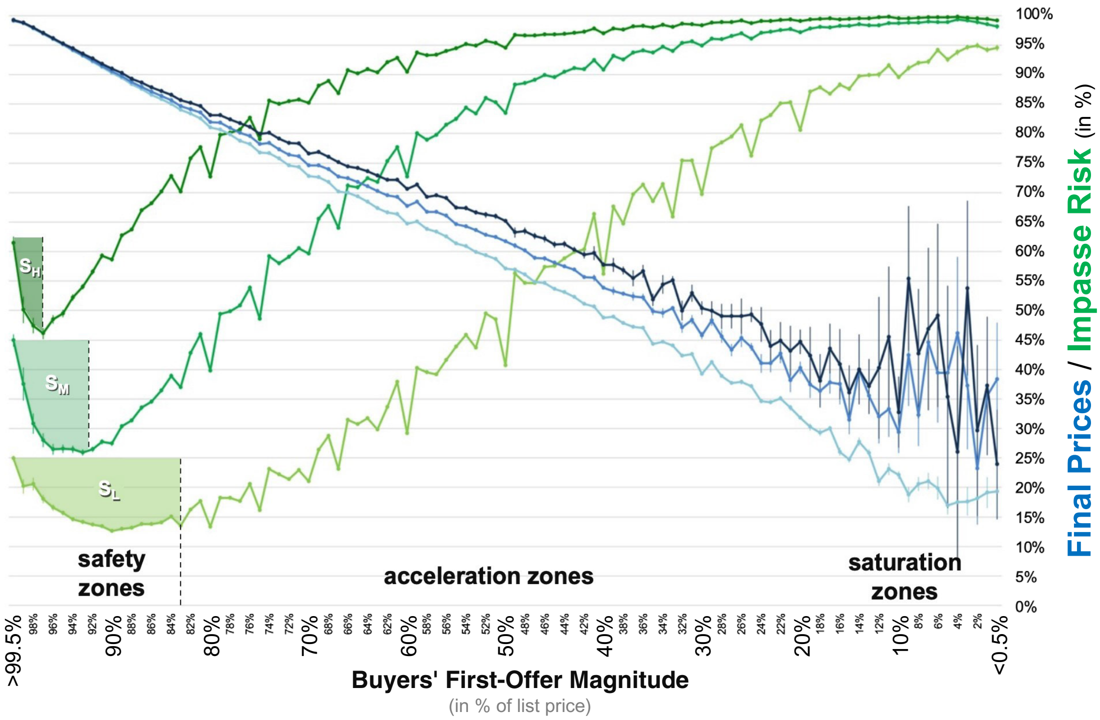

Fig. 3. Moderation by product demand. Note. Product demand moderates the (non)linear effects of first-offer magnitude (100% to 0%) on impasse risk (green) and final sales price (blue). Product demand increasingly narrows the impasse safety zones from low (S_L), to moderate (S_M) and high demand (S_H)—causing a faster acceleration and saturation of impasse risks. Product demand also moderates the linear anchoring effect on final price, with steeper regression slopes (i.e., stronger anchoring) for products with lower demand (lighter blue). Error bars constitute 95% CIs which are, at times, very short and barely visible.

offering more than the list price, negotiations with and without autoaccepted or autodeclined offers, sellers' and buyers' country (US versus non-US), their negotiation experience, the number of negotiation rounds, price level (<\$100 versus ≥\$100), and even versus odd list prices. 86 out of 88 (97.73%) replicated our main findings: (a) linear anchoring effects on price, (b) nonlinear effects on impasse risk, (c) local impasse optima, and (d) the buyer bias (see *SI Appendix*, Table S3 for a robustness overview).

Machine learning analyses (Python, scikit-learn module; 38) with the >26 million negotiations, a train-validation-test split and logistic regression classifiers (*SI Appendix*) showed that first-offer magnitude accurately predicted agreement versus impasse for 66% of ($F1_{NoDeal}$ = .70, $F1_{Deal}$ = .60, AUC = .72). Six additional predictors (i.e., negotiator experience and ratings on eBay, product condition and category, views per item, exchange of messages; *SI Appendix*, Table S14) improved the predictive validity to 72% correct classifications ($F1_{NoDeal}$ = .75, $F1_{Deal}$ = .68, AUC = .79). Finally, a histogram-based gradient boosting decision tree ensemble (39) with the same predictors further improved the predictive validity to 74% ($F1_{NoDeal}$ = .77, $F1_{Deal}$ = .70, AUC = .82).

Discussion

We leveraged incentivized, real-world negotiation data to dissect the first-offer conundrum, at least for negotiators in the buyer role in an online marketplace. Specifically, we integrated two previously separate literature streams investigating opposing effects and jointly explored the (non)linear effects of buyers' first offers on final price and impasse risk to identify an optimal first-offer value. Buyers on eBay who equally prioritize a low price and a low impasse risk should make a first offer at 80% of the seller's list price. This ideal offer minimizes both the impasse risk and final price paid (Fig. 1). The recommendation differs, however, across product categories and buyer demand (Fig. 2). For instance, in the art category, it is 75% of the list price, and for music, a product category with less demand, it is 65%. The ideal offer ranges from 33% (category: "miscellaneous") to 95% (category: "coins and paper money").

Finally, as Fig. 2 illustrates, the ideal offer also depends on how much buyers strive to avoid an impasse (versus achieve a low price). The absolutely lowest impasse risk emerges from a 90% offer (i.e., point of minimal risk in Fig. 1). Counterintuitively, this impasse risk is even lower than that for offers from 91% to >99.5%, as is reflected in the quartic function (see *safety zone*). Of course, negotiators who want to avoid an impasse altogether can always offer to pay full price immediately to avoid any negotiation, thus eliminating the impasse risk altogether. We also separately examined the relatively rare instances (n = 120,872; i.e., 0.46% of all negotiations), in which buyers made first offers *above* the seller's list price (i.e., >100%). Two noteworthy effects emerged (*SI Appendix*, Fig. S6): (a) a linear anchoring effect of buyer offers on final price, and (b) a uniformly *high* impasse risk (i.e., M = 73.55%), that is likely due to the interest of numerous negotiators bidding on the same product [similar to many housing markets, (40)]. Finally, the present data do not empirically support the well-known midpoint bias but show a buyer bias that ranges between 13.56% and 36.67% (30) that could be due to buyers offering (and thus losing) money to sellers who, in turn, perceive the same transaction as gaining money (29, 41).

Theoretical and Empirical Contributions.

Linearity and nonlinearity for first-offer anchoring and impasse risk. Research had yet to empirically examine the prominent but untested linearity assumptions regarding how increasingly ambitious offers (a) anchor final prices and (b) increase impasse risk. Prior studies (42) employed constrained study designs with insufficient granularity of first-offer magnitude and also frequently employed nonincentivized, simulated negotiation scenarios with limited ecological validity (33). Typically, prior studies examined

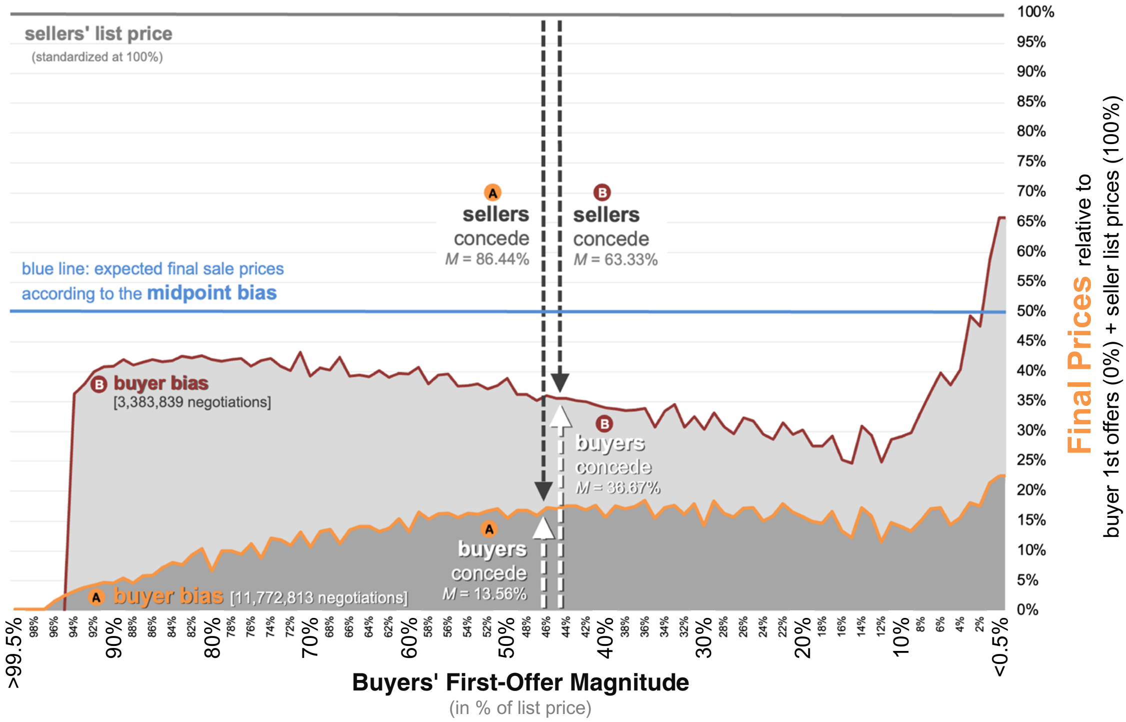

Fig. 4. Evidence for a buyer bias rather than the midpoint bias. Note. Final sales prices as a function of buyers' first-offer magnitude (ranging from 100% to 0%). (*A*) For all 11,772,813 negotiations that ended with a deal, sellers made significantly larger concessions (M = 86.44%) than buyers did (M = 13.56%; see orange line). (*B*) Even in only those 2,476,490 negotiations in which sellers decided to make a counteroffer, sellers continued to make larger concessions (M = 63.33%) than buyers did (M = 36.67%; see red line). Overall, the data reflect a strong buyer bias rather than the popular 50–50 "midpoint bias" (see blue line at 50%).

one moderate versus one extreme offer (left versus right side of the *x*-axis in Fig. 1) and interpreted the higher impasse risk of the more ambitious offers as evidence for a linear relationship between offer magnitude and impasse risk. Our paper challenges this notion and provides insights into the relationship of anchoring benefits and impasse-risk detriments across the full spectrum of first-offer magnitude.

Although the anchoring effect flattens out beyond certain thresholds in cognitive evaluation tasks (27), the first offer's anchoring impact on final prices revealed a strictly linear function that held across the full range of offers, from very moderate to very ambitious. The anchoring effect did not asymptotically flatten out beyond a certain threshold (e.g., refs. 28 and 43), provided an agreement was reached. Notably, the sale prices of less than 35% in the saturation zone of Fig. 1 stem from less than 10% of all negotiations that even reached an agreement.

Conversely, the effect of first offers on impasse risk was nonlinear. Contrary to the linearity assumption predicted by prior theorizing and expert scholars, our analysis establishes a robust quartic relationship between offer magnitude and impasse risk. This quartic function identifies three zones of distinct impasse risk—safety, acceleration, and a saturation zone (Figs. 1 and 3). The pattern of results is currently not accounted for by prior theorizing in the field (7–13), and further research is needed to examine the underlying psychological mechanisms that explain this quartic effect. For now, we can only argue that theorizing should be extended by both cognitive mechanisms and interpersonal perceptions. First, in terms of sellers' cognition, sellers who are offered (almost) their full list price may cognitively understand that their list price was not assertive enough. They may paradoxically regret having their first offer (almost) accepted (44), cognitively reassess the true value of their product, correct it upward, and consequently prefer an impasse over an agreement to then relist their product at a higher price. Second, in terms of interpersonal perceptions, it seems plausible that first offers just below the sellers' list price impair the interpersonal perception that sellers have of the opposing buyer [e.g., agency, communion; (45)]: Indeed, sellers may be (more) offended by arguably overassertive, proself, uncooperative buyers who seek to negotiate only a few percent off the (seemingly already fair) list price, say, between \$1 and \$9 for a product listed at \$100. Psychologically, because sellers' perceptions of buyers' agency and communion is impaired and because sellers are consequently more upset (12, 16) and more offended (13, 14) by offers closer to their list price, they may therefore prefer to refrain from reaching an agreement (46).

The acceleration zone (ranging from approx. 90% to 20%) reveals two patterns. First, the impasse risk steadily increases as first offers become more ambitious. Second, this steady acceleration is punctuated by salient drops with particularly low impasse risks (i.e., local optima). For example, buyers who offer 50% of the list price encounter a lower impasse risk than buyers who offer slightly less (49%) and even than those who offer slightly more (i.e., 51%). These drops are statistically identifiable through quantifying the deviation of data points from the LOWESS curve. We identified the five biggest drops below the quartic function, in decreasing order, at 60%, 50%, 80%, 75%, and 67% (2/3; *SI Appendix*, Table S7). These local optima occur at cognitively salient points for which fractions can be easily calculated (47, 48) and which are mentally easy to process. For instance, 67% constitutes two-thirds of the list price, e.g., a \$100 offer for a product listed at \$150. These easily calculated offers may facilitate acceptance (49). In contrast, more precise offers may seem more competently calculated (e.g., ref. 25), but may also make the offer-maker seem more inflexible (e.g., ref. 50), thus increasing the impasse risk compared to round offers. Our results support the impasse advantage of round, easily calculable offers (37), but future research should causally test the underlying psychological processes that account for these local impasse optima.

Finally, the impasse curve flattens in the saturation zone (beginning at approx. <20%), revealing a stable and high impasse risk. Around 95% of all these negotiations end in impasse, irrespective of whether buyers offer 15% or only 1% of the list price. In stark contrast, final prices, provided the offer is accepted, continue to decrease linearly as first offers become more ambitious. Hence, negotiators who are unconcerned about an impasse can make highly ambitious offers, even below 20%, to minimize the final sales price at a high but relatively stable impasse risk.

Applied Contributions. Negotiators everywhere ask themselves how high their first offer should be; yet this question has remained unanswered. Osório (3) described this first-offer conundrum as "an ancient and intriguing question, which seems to fascinate everybody." Practitioners familiar with first-offer research know that making the first offer is important (2, 5), but they do not know how high this offer should be. Recommendations have often been based on vague, imprecise, confusing, or even conflicting anecdotal evidence (*SI Appendix*, Table S1). We seek to help practicing negotiators by offering a free online calculator that recommends an optimal first offer as a function of a negotiator's individual risk preferences, product type, buyer demand, and sellers' list price (https://firstofferadvice.com/advice). Fig. 2 also illustrates how product demand and a negotiator's individual willingness to risk an impasse change recommended first offers.

Limitations and Avenues for Future Work. This research is not without limitations. While these large-scale data allowed us to identify both a linear anchoring and a nonlinear impasse effect, the data did not allow for experimental manipulation of factors to causally examine underlying mechanisms. Future studies should examine the underlying psychological processes (e.g., perceptions of regret, disappointment, offense, anger, or ease of cognitive processing) and test whether experimental interventions can, for instance, widen the range of impasse risk drops. For example, the impasse risk optimum around the 50% mark could be widened to 45%–55% by making range offers [*I'm offering $90 to $110*; (16)], providing rationales (51), utilizing first-offer framing effects (52), or by adding simple verbal description (e.g., *I'm offering $30; that's about one third of your $100 list price*) compared to stating the offer alone (*I'm offering $30*).

In addition, the relationship between first offers and impasses is likely different for services compared to products (53). Only two of the 34 categories in our dataset included services (i.e., specialty services, and business/industrial services). Many other negotiations are structurally different from buyers making their first offer in an online marketplace setting, such as face-to-face negotiations over cars (54), real estate (50), or salary negotiations (55). These could feature different ideal first-offer magnitudes and possibly different patterns of (non)linearity and local impasse optima. Future research should examine the impasse and anchoring effects in other real-world settings.

Conclusion

We integrate previously separate literatures on first-offer anchoring and impasses and use a large-scale dataset of incentivized real-world negotiations to establish linear anchoring and nonlinear, quartic impasse effects for first-offer magnitude. This integrative perspective yields an empirical answer to the persistent first-offer conundrum. Our results reveal a buyer bias (rather than the well-known midpoint bias), and show how buyer demand for products moderates these findings and (non)linearity functions. Finally, we offer evidence-based advice to help practitioners resolve the first-offer conundrum in their specific negotiation situations.

Methods

Dataset. The dataset was made available by Backus, Blake, Larsen, and Tadelis (56) and contains information about more than 28 million negotiations between buyers and sellers on eBay's Best Offer marketplace platform. Sellers first determine a list price for their product (i.e., the seller's first offer), and buyers initiate the negotiation with a counteroffer [i.e., the buyer's first offer; (57, 58)]. The original dataset contains information about 98,307,281 unique products across 34 categories (e.g., "art," "jewelry & watches," "computers & electronics"), including list price, reference price, product condition, delivery times, and product category. The data provide fine-grained information about 28,203,943 unique negotiations between one seller and one buyer for a specific product [e.g., offer values per round, agreement versus impasse, final price paid if agreement was reached; (56)]. Distributive, single-issue negotiations over price are common for consumers (59) and businesses (60).

Dataset Preparation. The original data consisted of two files: one containing information about the products offered and one containing information about each negotiation (combined file size: 18 gigabytes). We merged both files into a MySQL database and restructured the merged dataset so that each of the 28,203,943 rows represented one unique negotiation with 32 variables, including product-specific and situation-specific information (e.g., list prices and offers, agreement or impasse, final price, etc.). We analyzed the data with Python, using traditional and advanced machine learning algorithms. To help other scholars pursue similar research questions, we share extensive documentation, instructions, and code on how to analyze these data using Python and machine learning algorithms (https://osf.io/k3zax/).

We conducted robustness checks [similar to those employed by Backus, Blake, Larsen, and Tadelis; (56)] to eliminate errors and invalid offers. We applied six rules sequentially. For instance, we excluded negotiations in which the buyer's offer was higher than the seller's list price (n = 952,910; 3.38% of all negotiations). As eBay only allows for three rounds, we excluded the 0.03% (n = 8,803) of negotiations consisting of ≥4 rounds, which were likely included due to a technical glitch. In line with (56), we also excluded negotiations with high list prices due to presumably poor data quality (e.g., a $45 offer to a $68,000 list price was accepted). Our $2,500 threshold was more conservative than Backus et al.'s $1,000 cutoff. Importantly, all of the reported findings on the linear anchoring effect, the nonlinear impasse function, the local impasse optima, and the opening-offer buyer bias also emerged when negotiations with list prices >$2,500 were also included. In total, 6.2% of all negotiations were excluded (see *SI Appendix*, Table S2 for details). The final dataset contained 26,454,176 unique negotiations over 18,751,993 unique products across 34 product categories.

Variables. We created (and used) the following variables for our (machine learning) analyses (61).

Predictor: Buyers' first-offer magnitude. First, we created a standardized variable for buyers' first-offer magnitude by dividing buyers' first offer by sellers' list price and multiplying this by 100%.

$$Buyers'\ first\text{—}offer\ \ magnitude = \frac{buyers'\ first\ \ offer}{sellers'\ list\ \ price} \times 100\,\%.$$

Higher values indicate less assertive buyer offers. A first offer of, say, $90 for a product listed at $100 results in a value of 90%; an offer of $20 for the same product results in a value of 20%.

Dependent variable: Final sales price. Second, we created a standardized variable for final sales price by dividing the final price by the sellers' initial list price and multiplying this by 100%.

$$Final\ \ sales\ \ price\ \ (in\ \ \%) = \frac{final\ \ price}{sellers'\ list\ \ price} \times 100\,\%.$$

Higher values indicate final prices closer to sellers' list prices. For example, a final price of $75 and a list price of $100 results in a value of 75%, while a final price of $10 for the same product results in a value of 10%. Buyers' offer magnitude and sellers' claimed value can be easily compared because both are standardized based on the seller's list price. If a buyer offers $50 for a product with a $100 list price, and the final agreement is $75, the buyer's offer magnitude is 50%, and the final sales price is 75%. All negotiations that ended with an impasse have no values for this variable.

Dependent variable: Impasse risk. We operationalized impasse risk as the number of impasses divided by the number of negotiations as a function of buyers' first-offer magnitude (range: 0%–100%). For example, buyers started with an offer at 50% of the list price in 1,696,030 negotiations. Of these, 658,539 ended in a deal, and 1,037,491 in an impasse, resulting in an overall impasse risk of 1,037,491/ 1,696,030 × 100% = 61.17% (Fig. 1).

Analysis of the ideal first offer. To establish the ideal first offer, we needed to integrate the data for sales price and impasse risk. Hence, this analysis examined which buyer offer magnitude (in %) coincides with both the lowest sales price (blue data points) *and* the lowest impasse risk (green data points, Fig. 1)—thus quantifying the cumulative distance of both data points from the x-axis. The optimum was reached when no other buyer offer coincided with a combination of datapoints for price and impasse risk that was closer to the X-axis (i.e., lower price *and* lower impasse risk). If individual negotiators place more importance on a low(er) impasse risk, the first-offer recommendation is adjusted accordingly (see https://firstofferadvice.com/advice).

Moderator: Buyers' product demand. We operationalized buyers' product demand by counting the number of unique bidders per product ($M = 2.23$, $SD = 2.52$, $min = 1$; $max = 119$). As many products had only one or two bidders, we classified negotiations with one bidder as low demand ($N = 14{,}405{,}766$), negotiations with two bidders as medium demand ($N = 5{,}505{,}352$), and negotiations with three or more bidders as high demand ($N = 6{,}543{,}058$).

Machine Learning Analyses. We conducted machine learning analyses using Python's scikit-learn module (38). We used general logistic regression classifiers as baseline models, and then trained a more complex machine learning algorithm using histogram-based gradient boosting decision tree classifiers (39) to predict which individual negotiations end in agreement versus with an impasse (binary variable). This algorithm can be efficiently trained to capture complex data structures. For all models, we conducted a train-validation-test split with grid search to choose suitable model hyperparameters: e.g., a regularization parameter (range: 0.01 to 10, best parameter = 1), learning rate (range: 0.01 to 1, best parameter = 0.1), and maximum decision tree depth (range: 10 to 50, best parameter = 25). We evaluated the model on a separate test set previously unknown to the trained model (i.e., 80% training, 10% validation, 10% testing). Model performance is reported for the final test set. In addition, we used all seven predictors (i.e., first-offer magnitude, negotiator experience and ratings on eBay, product condition and category, views per item, exchange of messages) in a histogram-based gradient boosting decision tree ensemble (39). This algorithm sequentially combines separate decision trees of limited depth, with each additional tree correcting the prediction errors made by the previous ensemble (i.e., minimizing training error). Individual tree predictions are summed up to an overall ensemble prediction (i.e., deal versus impasse as a binary outcome for each negotiation).

Data, Materials, and Software Availability. These data were developed as part of the NSF Project #1629060 "Bilateral Bargaining through the Lens of Big Data." They have been cleared for public release by eBay.com and are available for research purposes. All data have been deposited in NBER: National Bureau of Economic Research (https://www.nber.org/research/data/best-offer-sequential-bargaining) (62). All personally identifying information has been removed. All study data are included in the article and/or *SI Appendix*.

ACKNOWLEDGMENTS. We would like to thank the members of the School of Management and Technology at Leuphana University and the Department of Organizational Behavior at ESMT Berlin for the helpful comments on this research, Katherine L. McLain, Zainab Mohamed, and Hai Anh Vu for their research assistance, as well as Keri Hartman, Benjamin W. Walker, and Paul Lauer for editing and proofreading the manuscript. We thank Backus, Blake, Larsen, and Tadelis for openly sharing their dataset.

Author affiliations: [a]Organizational Behavior Department, ESMT Berlin, 10178 Berlin, Germany; [b]Institute of Management and Organization, Leuphana University Lueneburg, 21335 Lueneburg, Germany; and [c]Institute of Information Systems, Leuphana University Lueneburg, 21335 Lueneburg, Germany

1. A. D. Galinsky, M. E. Schweitzer, *Friend and Foe: When to Cooperate, When to Compete, and How to Succeed at Both* (Crown Business, 2015).
2. D. D. Loschelder, R. Trötschel, R. I. Swaab, M. Friese, A. D. Galinsky, The information-anchoring model of first offers: When moving first helps versus hurts negotiators. *J. Appl. Psychol.* **101**, 995–1012 (2016).
3. A. Osório, On the first-offer dilemma in bargaining and negotiations. *Theory Decis.* **89**, 179–202 (2020).
4. J. M. Chertkoff, M. Conley, Opening offer and frequency of concession as bargaining strategies. *J. Pers. Soc. Psychol.* **7**, 181–185 (1967).
5. A. D. Galinsky, T. Mussweiler, First offers as anchors: The role of perspective-taking and negotiator focus. *J. Pers. Soc. Psychol.* **81**, 657–669 (2001).
6. B. C. Gunia, R. I. Swaab, N. Sivanathan, A. D. Galinsky, The remarkable robustness of the first-offer effect: Across culture, power, and issues. *Pers. Soc. Psychol. Bull.* **39**, 1547–1558 (2013).
7. V. M. Bennett, Organization and bargaining: Sales process choice at auto dealerships. *Manage. Sci.* **59**, 2003–2018 (2013).
8. T. Mussweiler, F. Strack, T. Pfeiffer, Overcoming the inevitable anchoring effect: Considering the opposite compensates for selective accessibility. *Pers. Soc. Psychol. Bull.* **26**, 1142–1150 (2000).
9. A. Tversky, D. Kahneman, Judgment under uncertainty: Heuristics and biases. *Science* **185**, 1124–1131 (1974).
10. C. Janiszewski, D. Uy, Precision of the anchor influences the amount of adjustment. *Psychol. Sci.* **19**, 121–127 (2008).
11. N. Epley, T. Gilovich, Putting adjustment back in the anchoring and adjustment heuristic: Differential processing of self-generated and experimenter-provided anchors. *Psychol. Sci.* **12**, 391–396 (2001).
12. M. L. Frech, D. D. Loschelder, M. Friese, How attribution-of-competence and scale-granularity explain the anchor precision effect in negotiations and estimations. *Soc. Cogn.* **38**, 40–61 (2020).
13. M. Schweinsberg, S. Thau, M. M. Pillutla, Negotiation Impasses: Types, causes, and resolutions. *J. Manage.* **48**, 49–76 (2022).
14. A. Jager, D. D. Loschelder, M. Friese, How self-regulation helps to master negotiation challenges: An overview, integration, and outlook. *Eur. Rev. Soc. Psychol.* **26**, 203–246 (2015).
15. M. Schweinsberg, G. Ku, C. S. Wang, M. M. Pillutla, Starting high and ending with nothing: The role of anchors and power in negotiations. *J. Exp. Soc. Psychol.* **48**, 226–231 (2012).
16. D. R. Ames, M. F. Mason, Tandem anchoring: Informational and politeness effects of range offers in social exchange. *J. Pers. Soc. Psychol.* **108**, 254–274 (2015).
17. B. L. Leveck, D. A. Hughes, J. H. Fowler, E. Hafner-Burton, D. G. Victor, The role of self-interest in elite bargaining. *Proc. Natl. Acad. Sci. U.S.A.* **111**, 18536–18541 (2014).
18. H. Raiffa, *The Art and Science of Negotiating* (Harvard University Press, Cambridge, MA, 1982).
19. M. Jeong, J. A. Minson, F. Gino, In generous offers I trust: The effect of first-offer value on economically vulnerable behaviors. *Psychol. Sci.* **31**, 644–653 (2020).
20. M. M. Pillutla, J. K. Murnighan, Unfairness, anger, and spite: Emotional rejections of ultimatum offers. *Organ. Behav. Hum. Decis. Processes* **68**, 208–224 (1996).
21. J. Lammers, J. Crusius, A. Gast, Correcting misperceptions of exponential coronavirus growth increases support for social distancing. *Proc. Natl. Acad. Sci. U.S.A.* **117**, 16264–16266 (2020).
22. G. B. Northcraft, M. A. Neale, Experts, amateurs, and real estate: An anchoring-and-adjustment perspective on property pricing decisions. *Organ. Behav. Hum. Decis. Processes* **39**, 84–97 (1987).
23. T. Mussweiler, F. Strack, The semantics of anchoring. *Organ. Behav. Hum. Decis. Processes* **86**, 234–255 (2001).
24. M. Schaerer, R. I. Swaab, A. D. Galinsky, Anchors weigh more than power: Why absolute powerlessness liberates negotiators to achieve better outcomes. *Psychol. Sci.* **26**, 170–181 (2015).
25. D. D. Loschelder, M. Friese, M. Schaerer, A. D. Galinsky, The Too-much-precision effect: When and why precise anchors backfire with experts. *Psychol. Sci.* **27**, 1573–1587 (2016).
26. C. K. Hsee, Y. Rottenstreich, Music, Pandas, and Muggers: On the affective psychology of value. *J. Exp. Psychol. General* **133**, 23–30 (2004).
27. G. B. Chapman, E. J. Johnson, The limits of anchoring. *J. Behav. Decis. Making* **7**, 223–242 (1994).
28. T. Schultze, D. D. Loschelder, How numeric advice precision affects advice taking. *J. Behav. Decis. Making* **34**, 303–310 (2021).
29. M. A. Neale, V. L. Huber, G. B. Northcraft, The framing of negotiations: Contextual versus task frames. *Organ. Behav. Hum. Decis. Processes* **39**, 228–241 (1987).
30. M. A. Neale, G. B. Northcraft, Experts, amateurs, and refrigerators: Comparing expert and amateur negotiators in a novel task. *Organ. Behav. Hum. Decis. Processes* **38**, 305–317 (1986).
31. M. A. Marechal, C. Thöni, Hidden persuaders: Do small gifts lubricate business negotiations? *Manage. Sci.* **65**, 3877–3888 (2019).
32. C. F. Camerer, Removing financial incentives demotivates the brain. *Proc. Natl. Acad. Sci. U.S.A.* **107**, 20849–20850 (2010).
33. E. Schulz *et al.*, Structured, uncertainty-driven exploration in real-world consumer choice. *Proc. Natl. Acad. Sci. U.S.A.* **116**, 13903–13908 (2019).
34. A. Leibbrandt, J. A. List, Do women avoid salary negotiations? Evidence from a large-scale natural field experiment. *Manage. Sci.* **61**, 2016–2024 (2015).
35. M. Jeong, J. Minson, M. Yeomans, F. Gino, Communicating with warmth in distributive negotiations is surprisingly counterproductive. *Manage. Sci.* **65**, 5813–5837 (2019).
36. C. A. Moss-Racusin, J. F. Dovidio, V. L. Brescoll, M. J. Graham, J. Handelsman, Science faculty's subtle gender biases favor male students. *Proc. Natl. Acad. Sci. U.S.A.* **109**, 16474–16479 (2012).
37. H. M. Petrowsky, M. Schweinsberg, L. Seitz, B. Funk, D. D. Loschelder, Deal or no deal? The effect of round first-offer shares and precision mimicry on impasse risk in over 25 million eBay negotiations. *J. Econ. Psychol.* **94**, 102584 (2023).
38. F. Pedregosa *et al.*, Scikit-Learn: Machine learning in Python. *J. Mach. Learn. Res.* **12**, 2825–2830 (2011).

39. G. Ke *et al.*, LightGBM: A highly efficient gradient boosting decision tree. *Adv. Neural Inf. Process. Syst.* **30**, 3146–3154 (2017).
40. M. Leib, N. C. Köbis, M. Francke, S. Shalvi, M. Roskes, Precision in a seller's market: Round asking prices lead to higher counteroffers and selling prices. *Manage. Sci.* **67**, 1048–1055 (2021).
41. R. Trötschel, D. D. Loschelder, B. P. Höhne, J. M. Majer, Procedural frames in negotiations: How offering my resources versus requesting yours impacts perception, behavior, and outcomes. *J. Pers. Soc. Psychol.* **108**, 417–435 (2015).
42. D. Jang, H. A. Elfenbein, W. P. Bottom, More than a phase: Form and features of a general theory of negotiation. *Acad. Manage. Ann.* **12**, 318–356 (2018).
43. C. K. Hsee, Y. Rottenstreich, Z. Xiao, When is more better? On the relationship between magnitude and subjective value. *Curr. Dir. Psychol. Sci.* **14**, 234–237 (2005).
44. A. D. Galinsky, V. L. Seiden, P. H. Kim, V. H. Medvec, The dissatisfaction of having your first offer accepted: The role of counterfactual thinking in negotiations. *Pers. Soc. Psychol. Bull.* **28**, 271–283 (2002).
45. A. E. Abele, B. Wojciszke, Agency and communion from the perspective of self versus others. *J. Pers. Soc. Psychol.* **93**, 751–763 (2007).
46. K. Binmore, Bargaining and fairness. *Proc. Natl. Acad. Sci. U.S.A.* **111**, 10785–10788 (2014).
47. D. W. Braithwaite, R. S. Siegler, Children learn spurious associations in their math textbooks: Examples from fraction arithmetic. *J. Exp. Psychol.: Learn., Mem., Cognit.* **44**, 1765–1777 (2018).
48. B. A. Converse, P. J. Dennis, The role of "Prominent Numbers" in open numerical judgment: Strained decision makers choose from a limited set of accessible numbers. *Organ. Behav. Hum. Decis. Processes* **147**, 94–107 (2018).
49. D. Yan, J. Pena-Marin, Round off the bargaining: The effects of offer roundness on willingness to accept. *J. Consum. Res.* **44**, 381–395 (2017).
50. A. J. Lee, D. D. Loschelder, M. Schweinsberg, M. F. Mason, A. D. Galinsky, Too precise to pursue: How precise first offers create barriers-to-entry in negotiations and markets. *Organ. Behav. Hum. Decis. Processes* **148**, 87–100 (2018).
51. A. J. Lee, D. R. Ames, "I Can't Pay More" versus "It's Not Worth More": Divergent effects of constraint and disparagement rationales in negotiations. *Organ. Behav. Hum. Decis. Processes* **141**, 16–28 (2017).
52. J. M. Majer, R. Trötschel, A. D. Galinsky, D. D. Loschelder, Open to offers, but resisting requests: How the framing of anchors affects motivation and negotiated outcomes. *J. Pers. Soc. Psychol.* **119**, 582–599 (2020).
53. E. Hart, M. E. Schweitzer, Getting To less: When negotiating harms post-agreement performance. *Organ. Behav. Hum. Decis. Processes* **156**, 155–175 (2020).
54. A. Chandra, S. Gulati, J. M. Sallee, Who loses when prices are negotiated? An analysis of the new car market. *J. Ind. Econ.* **Lxv**, 235–274 (2017).
55. R. L. Pinkley, G. B. Northcraft, *Get Paid What You're Worth* (St. Martin's Press, 2000).
56. M. Backus, T. Blake, B. Larsen, S. Tadelis, Sequential Bargaining in the field: Evidence from millions of online bargaining interactions. *Q. J. Econ.* **135**, 1319–1361 (2020).
57. H. Raiffa, J. Richardson, D. Metcalfe, *Negotiation Analysis* (Belknap Press of Harvard University Press, Cambridge, MA, 2007).
58. S. Blount, Whoever said that markets were fair? *Negotiation J.* **16**, 237–252 (2000).
59. T. Marks, "Let's make a deal" in *Consumer Reports* (Consumers Union of United States, NY, 2013).
60. J. Wieseke, S. Alavi, J. Habel, Willing to pay more, eager to pay less: The role of customer loyalty in price negotiations. *J. Mark.* **78**, 17–37 (2014).
61. A. Zheng, A. Casari, "Feature engineering for machine learning" in *Principles and Techniques for Data Scientists* (O'Reilly Media, 2018).
62. M. Backus, T. Blake, B. Larsen, S. Tadelis, Best offer sequential bargaining. NBER. https://www.nber.org/research/data/best-offer-sequential-bargaining. Accessed 1 October 2020.
63. G. Ku, A. D. Galinsky, J. K. Murnighan, Starting low but ending high: A reversal of the anchoring effect in auctions. *J. Pers. Soc. Psychol.* **90**, 975–986 (2006).