The Conundrum of First-Offer Magnitude: Nonlinear and Linear Effects on Impasses and Sale Price in 25 Million Real-World Negotiations

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Abstract. How high should the first offer be? Prior to any negotiation, decision-makers must balance the tradeoff between two opposing first-offer effects. On the one hand, more assertive first offers benefit negotiators by anchoring the negotiation in their favor. On the other hand, a first offer that is too assertive increases impasse risk. Past research has demonstrated either the first offer's anchoring benefits (while largely ignoring the risk of impasse) *or* its impasse risk (while largely ignoring anchoring benefits). The literature also frequently builds on simulated laboratory or classroom scenarios and has yet to provide an empirical, applied answer to the question of how high the ideal first offer should be. We integrate these separate literature streams and establish, based on over 25 million incentivized real-world sales negotiations, (1) a linear anchoring effect of first offers on sale prices and (2) a nonlinear quartic effect on impasse prevalence. We further identify three magnitude zones with distinct first-offer effects, identify specific points with particularly low impasse risks and high anchoring benefits, empirically examine the opening-offer midpoint bias—the assumption that buyer and seller eventually meet in the middle of their opening offers—and establish moderation by price certainty and product demand (the impasse risk decreases, the more uncertain a product's objective value is and the fewer potential buyers are interested). Finally, we apply machine learning analyses to predict agreements and impasses and present a website that provides first-offer advice configurable to negotiators' particular product, list price, and risk preferences.

Key words: negotiation, first offer, impasses, anchoring

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Your first offer should be just this side of crazy, as opposed to that side of crazy.
— Galinsky and Schweitzer 2015, p.252

1. Introduction

Negotiators everywhere have to decide: How high should my first offer be? The conundrum is identifying "this side of crazy" versus "that side of crazy" (see Galinsky and Schweitzer 2015, p.252): On the one hand, ambitious first offers help negotiators claim value by favorably anchoring the counterpart (Chertkoff and Conley 1967, Galinsky and Mussweiler 2001, Bennett 2013, Gunia et al. 2013, Loschelder et al. 2016)—causing the final price to be lower for the buyer and higher for the seller. First offers serve as anchors either by selectively making anchor-consistent information accessible (Mussweiler et al. 2000, Galinsky and Mussweiler 2001), or by causing recipients to insufficiently adjust their counteroffers away from the anchor (Tversky and Kahneman 1974, Epley and Gilovich 2001, Janiszewski and Uy 2008, Frech et al. 2020). However, negotiators systematically underestimate the size of the bargaining zone (Larrick and Wu 2007), suggesting that many first offers are not ambitious enough. On the other hand, ambitious first offers increase the risk of an impasse—no deal whatsoever (Schweinsberg et al. 2012, 2022, Ames and Mason 2015). An offer that is too ambitious and on "that side of crazy" upsets the counterpart (Raiffa 1982, chapter 9), destroys trust (Jeong et al. 2020), violates expectations of appropriate behavior (Pillutla and Murnighan 1996), and causes offence, increasing the risk of an impasse (Schweinsberg et al. 2012).

To quantify this first-offer conundrum, we reviewed management guidebooks on negotiations and peer-reviewed articles[1], consulted 35 established negotiation scholars with 12.88 years of experience ($SD = 7.98$), and conducted a literature search for advice from practicing experts. Strong consensus emerged that negotiators should "open ambitiously, but not *too* ambitiously" (Table S1 in the Supplementary Online Materials (SOM) on OSF): the sample of expert scholars overwhelmingly agreed with this statement ($M = 5.51$, $SD = 1.31$ on a 7-point scale; $t_{\text{scale-mean}}[34] = 6.81$, $p <.001$, $d = 1.15$). Nonetheless, the line between "this and that side of crazy" remains largely unclear (Table S1). When is a first offer "too ambitious"? The heterogeneous range and lack of clarity was illustrated by our expert sample, who advised buyers to make first offers ranging from 15%–100% of the seller's list price ($M = 59.94\%$), with an $SD = 23.74\%$. In sum, practitioners rely on academic advice that is, at times, unclear and vague (Table S1, sources #3, #9–11), void of empirical evidence (sources #1–2, #4–7, #12–13), and potentially even conflicting (sources #11 & #14).

[1] To our knowledge, no peer-reviewed articles have examined or quantified how high the 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.

Not only has the literature yet to offer precise advice on first-offer magnitude, there is also no empirical evidence for two prominent but untested assumptions of linearity. We do not know whether increasingly ambitious first offers (1) exert a linearly more potent anchoring effect, and (2) whether they are related linearly to a higher risk of impasse. Existing studies, however, are predominantly based on these linearity assumptions (Lammers et al. 2020). Our expert sample also strongly agreed with this assumption of a linear impasse risk ($M = 5.34$, $SD = 1.53$; $t_{\text{scale-mean}}[34] = 5.18$, $p <.001$, $d = 0.88$). To the best of our knowledge, the literature has yet to empirically examine either of these linearity assumptions in a sufficiently fine-grained way. However, related findings suggest potential nonlinearity. Participants in economic games reject seemingly unfair offers in a nonlinear fashion if these offers are just below a perceived meaningful standard (Pillutla and Murnighan 1996), and previous research has documented nonlinear relationships between negotiators' alternatives and their first-offer magnitude (Schaerer et al. 2015), as well as between first-offer precision and anchor potency (Loschelder et al. 2016). It is plausible that negotiators' subjective reactions to increasingly assertive offers are also nonlinear (see Hsee and Rottenstreich 2004): For instance, anchoring effects might level off at a certain point (Chapman and Johnson 1994), asymptotically reaching a maximal anchoring effect (see Schultze and Loschelder 2021).On the other hand, the impasse risk might only begin to increase once a certain threshold of offer magnitude is reached and might level off again after surpassing a certain level of excessive ambition. These forms of nonlinearity would expand our theoretical understanding of first-offer effects and help practitioners decide on a first offer that maximizes value whilst minimizing impasse risk.

Finally, our research empirically tests the prominent assumption of *opening-offer midpoint bias*, which posits that negotiators (e.g., buyer and seller) are likely to agree on a final deal close to the midpoint of their opening offers (Galinsky and Schweitzer 2015, p. 253; Raiffa 1982, chapters 4 & 9). Despite its prominence among scholars and practitioners, to our knowledge, no prior empirical work has tested or confirmed this assumption. Examining the first-offer conundrum, linearity assumptions, and opening-offer midpoint bias requires enormous data sets with continuous variation in offer magnitude, ideally real-world incentives (Maréchal and Thöni 2019), as well as information on parties' opening offers, final prices, and the resulting impasse likelihood.

In this paper, we integrate the distinct lines of research on first-offer anchoring and impasses and empirically examine the untested assumptions of linearity and midpoint bias by analyzing 26,454,176 incentivized, real-world sales negotiations (see Leibbrandt and List 2015, Jeong et al. 2019). Linear and logistic regressions, as well as machine learning analyses, allow us to quantify when the anchoring benefits of first offers outweigh the impasse risk to empirically test prior assumptions of linearity and midpoint bias, to examine moderation by price certainty and buyer demand, and to create machine learning-based classification models for predicting deals or impasses.

Building on these analyses, we created a website (https://www.firstofferadvice.com) that provides negotiators with recommendations for the magnitude of their first offer, configurable to their specific list price, product type, and their risk tolerance for impasses. This website translates our empirical findings into evidence-based first-offer recommendations for practitioners.

2. Method

2.1. Data Set

The data set was made available by Backus et al. (2020) and contains information about more than 28 million negotiations between buyers and sellers on eBay's Best Offer marketplace platform. Businesses increasingly negotiate on marketplace platforms, making this a suitable empirical setting to study first-offer effects (Parker et al. 2016). Sellers determine a list price for their product, and buyers initiate the negotiation with a first offer. The negotiation ends after a maximum of three rounds of offers and counteroffers with either agreement on a final price or an impasse. Sellers can simultaneously negotiate with multiple buyers for the same product.

The original data contains information about 98,307,281 unique products across 34 categories (e.g., "art", "jewelry & watches", and "computers & electronics"), including list price, reference price, product condition, delivery times, and product category. The data also provides more 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 vs. impasse, final price paid if an agreement was reached, etc.; see Backus et al. 2020). Distributive, single-issue negotiations over price are common for consumers (Marks 2013) and businesses (Wieseke et al. 2014). Our findings and recommendations are based on these sales negotiation data from eBay's marketplace platform; future research should replicate and generalize these results to other domains, contexts, and platforms (see Discussion).

2.2. Data Set 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 data set so that each of the 28,203,943 rows represented one unique negotiation with 32 variables, including product-specific and situation-specific variables (e.g., list prices and offers, agreement or impasse, final price, etc.). We analyzed the data with Python.

We conducted robustness checks (similar to those employed by Backus et al. (2020) to eliminate errors and invalid offers. We applied six rules sequentially: the first rule excludes negotiations in which the buyer's offer was higher than the seller's list price (n = 952,910, or 3.38% of all negotiations in the data set). We also excluded the 0.03% (n = 8,803) of negotiations consisting of four or more rounds.As eBay only allows three negotiation rounds, these negotiations were likely included due to a technical glitch. 6.2% of all negotiations were excluded (for details, see Table S2 in the SOM). The final data set contained 26,454,176 unique negotiations over 18,751,993 unique products across 34 product categories. We provide instructions and Python scripts to help other scholars use these data and analytical techniques in their own research (OSF).

2.3. New Variables

We created several variables for our (machine learning) analyses (Zheng and Casari 2018).

2.3.1. 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:

$$Buyers' \textit{ first-offer magnitude} = \frac{buyers' \textit{ first offer}}{sellers' \textit{ list price}} \times 100$$

Higher values indicate less assertive first 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.

2.3.2. Dependent Variable: Sellers' Claimed Value. Second, we created a standardized variable for "sellers' claimed value" to measure how much of the initial list price sellers ended up claiming, by dividing the final agreement price by sellers' initial list price:

$$Sellers' \textit{ claimed value} = \frac{\textit{final price}}{sellers' \textit{ list price}} \times 100$$

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 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 seller's claimed value is 75.

2.3.3. 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 (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 $\frac{1{,}037{,}491}{1{,}696{,}030} = 61.17\%$ when buyers open with an offer of 50% of the list price (Figure 1).

2.3.4. Moderator: Price Certainty. We created a measure of price certainty to capture how confident negotiators are of the appropriate price for different products. People are more certain about the prices of some products (e.g., mobile phones) than of other products (e.g., art). Price certainty is relatively high when multiple buyers' first offers are all within a narrow range (i.e., \$500, \$490, \$480, \$475, and \$470; SD = 12.04) and price certainty is relatively low when buyers' first offers are diverse across a wide range of offers (i.e., \$600, \$450, \$250, \$120, and \$90; SD = 218.79). Our price certainty variable has three levels (low, medium, and high) and was created using information in the data set. This helped us avoid potentially inaccurate, outdated, or non-applicable external price certainty standards. We operationalized price certainty as first-offer variance per product category: we (1) aggregated the mean standard deviations (*SD*s) of first offers for each product and (2) calculated mean *SD*s per product category. To ensure reliability, we only included products with at least three interested buyers to adequately measure first-offer variance (and ultimately price certainty).

$$Price\ certainty = \frac{\sum SD\ of\ buyers'\ offers\ per\ product}{number\ of\ products\ in\ category}$$

We then created quartiles for price certainty scores per product category and assigned three levels of price certainty: high price certainty products are in the top quartile (e.g., cellphones, cameras, gift cards), medium price certainty in the second and third quartiles (e.g., clothing, toys, stamps), and low certainty products in the bottom quartile (e.g., art, antiques, entertainment memorabilia; for details on product categories and quartile computation, see OSF).

2.3.5. Moderator: Product Demand. We operationalized product demand by counting the number of unique bidders per product ($M = 2.23$, $SD = 2.52$; $min = 1$, $max = 119$). Many products had only one or two bidders, so we did not segment product demand into quartiles. Instead, 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).

3. Analyses and Results

3.1. Linear First-Offer Effects on Final Sale Price

We examined the effects of buyers' first-offer magnitude on sellers' claimed value in two steps. First, we clustered negotiations based on buyers' first-offer magnitude in ranges of 1% (e.g., all negotiations that involve a first offer in the range of ≥49.50% to <50.50% of the list price are clustered into the 50% first-offer magnitude range). Second, we calculated the mean sellers' claimed value for all negotiations within a range (e.g., mean sellers' claimed value in the 50% offer-magnitude group

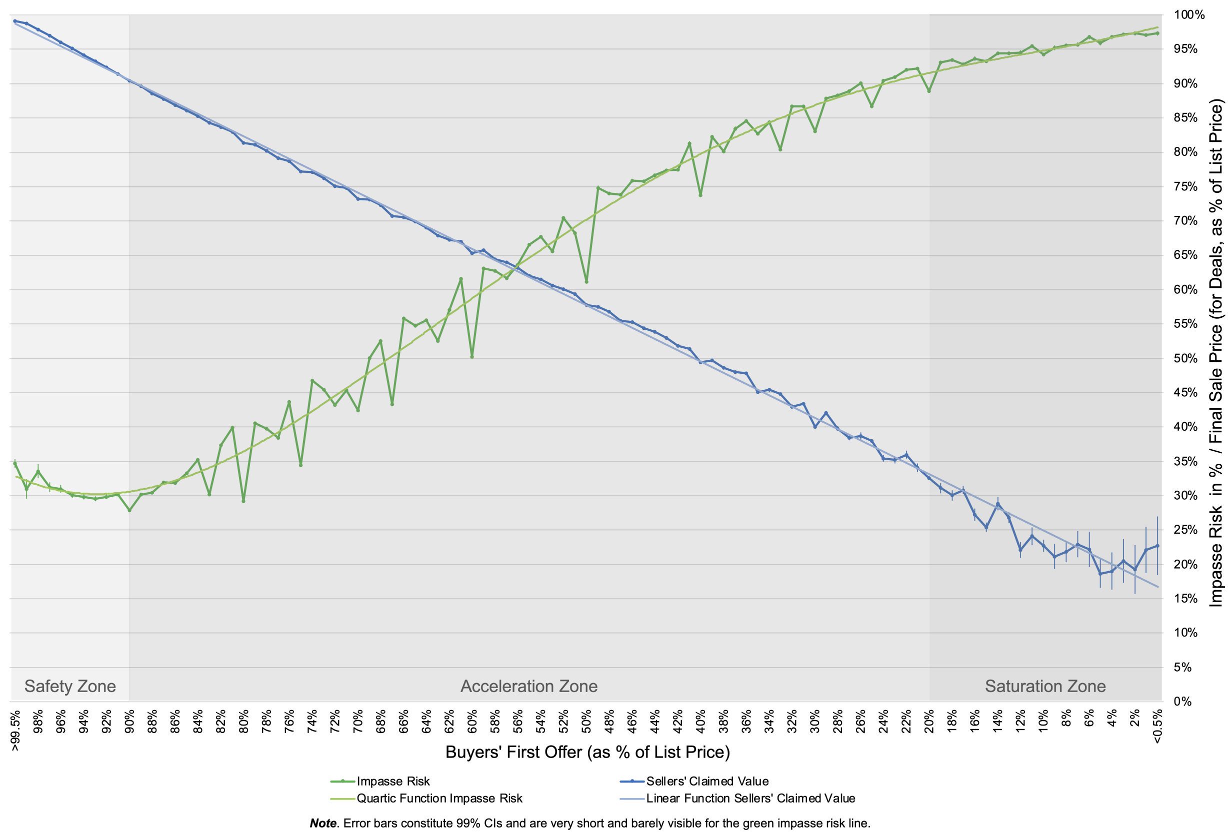

Figure 1 Impasse Risk and Final Sale Price as a Function of Buyers' First-Offer Magnitude (in Steps of 1%).

is 57.74%), and regressed mean sellers' claimed value on buyers' first-offer magnitude ranges. This regression led to a fit of $R^2 = .997$, $b = 0.82$, $F(1{,}99) = 35{,}589.63$ (SOM Table S3). Adding higher-order polynomials (i.e., quadratic, cubic, quartic) did not increase model fit ($\Delta R^2 = .000$), suggesting a fully linear anchoring effect (Figure 1; blue line): increasingly assertive first offers resulted in increasingly lower final sale prices unless they caused an impasse. We replicated these results when we re-ran the analysis predicting final prices individually for each of the 11,772,813 successful negotiations (excluding 14,681,363 negotiations that ended with an impasse): buyers' first-offer magnitude again had a strong linear effect on final prices, $R^2 = .727$, $b = 0.81$, $F(1{,}11{,}772{,}811) = 31{,}265.658.69$, $RMSE = 7.63$. Again, adding higher-order polynomials did not increase the model fit ($\Delta R^2 = .000$), confirming the fully linear anchoring effect. For first-offer effects on impasse risk see section 3.3.

3.2. Midpoint Bias of Opening Offers

We then probed the data for empirical evidence of the midpoint bias using a train-validation-test split approach. We regressed final sale prices on both sellers' list price and buyers' first-offer magnitude. We again excluded impasses and only included products with a reliable reference price (i.e., computed from multiple deals; $N = 256{,}830$). Sellers' list price alone explained $R^2 = .168$

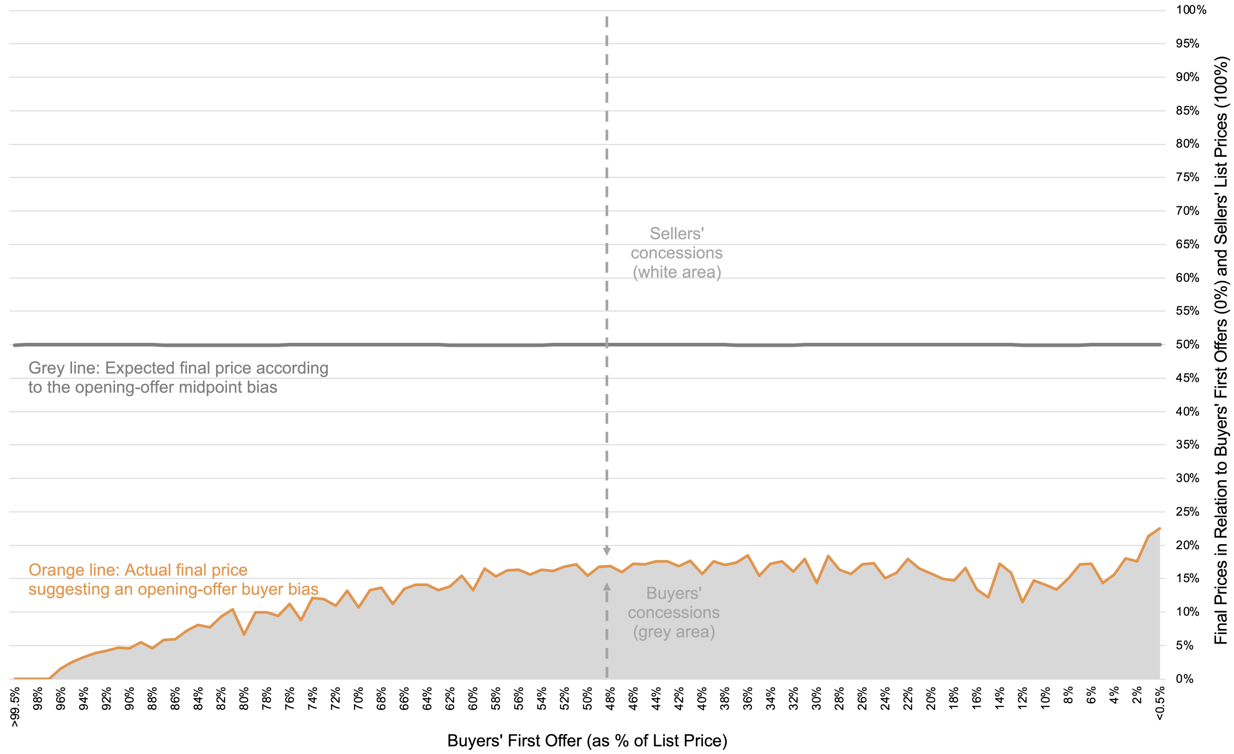

Figure 2 **Empirical Evidence for an Opening-Offer Buyer Bias.**

of the variance in final prices (b = 0.14, $RMSE$ = 32.20). Adding buyers' first-offer magnitude substantially increased the explained variance to $R^2 = .929$ ($RMSE = 9.39$). The marked increase in predictive power ($\Delta R^2 = .761$) and in model fit ($\Delta RMSE = -22.81$) suggests that buyers' offer magnitude is relatively more influential than sellers' list price. Figure 2 confirms this, as for all 14.68 million negotiations with an agreement, final sale prices (orange line) were much closer to buyers' offers (0% on y-axis) than to sellers' list prices (100% on y-axis), suggesting that buyers conceded less from their opening offers (grey area) than sellers did (white area). The data speak against an opening-offer midpoint bias (50% on y-axis) and instead suggest a pronounced buyer bias. This buyer bias was stronger, the lower demand there was for a product from other interested buyers (SOM Figure S4).

3.3. Nonlinear First-Offer Effects on Impasse Likelihood

For the likelihood of impasses, our analyses established nonlinear effects of first-offer magnitude: Figure 1 (green line) shows the impasse rates across the entire range of first offers. A linear regression with buyers' first-offer magnitude as predictor resulted in a fit of $R^2 = .959$—more assertive offers caused more impasses. However, a strictly linear model does not capture any of the nonlinear aspects observed in Figure 1. In subsequent analyses, we added polynomials and empirically established nonlinearity with improved model fits of $R^2 = .966$ (quadratic model) and $R^2 = .985$ (cubic model). The highest fit, however, emerged for a quartic model, $R^2 = .988$; this model is depicted as the light green function in Figure 1 (i.e., 4^{th} order polynomial; see Table S4). A fifth-order polynomial did not increase the model fit ($\Delta R^2 = .000$). From left to right, the impasse risk first decreased slightly (*safety zone*), then increased (*acceleration zone*) until it leveled off after having reached a threshold of assertiveness (*saturation zone*). Our regression- and tree-based machine learning algorithms to predict deals and impasses reached acceptable to excellent prediction scores (SOM). We based the applied negotiation advice on our website on these analyses.

3.4. Local Impasse Optima

A close inspection of Figure 1 also reveals robust local optima, specific values of buyers' offer magnitude that coincide with a markedly reduced impasse risk. These optima are visible for offers of 90%, 83%, 80%, 75%, 70%, 67%, 60%, 50%, 40%, 33%, 30%, 25%, and 20% of the sellers' initial list price (green drops below the quartic function). Additional robustness checks confirmed that these local impasse optima also occurred when excluding round list prices (i.e., prices divisible by 5 without remainder, e.g., $100.00, $95.00, $90.00, etc.), when excluding round first offers (i.e., offers divisible by 5 without remainder, e.g., $100.00, $95.00, $90.00, etc.), and when excluding both (SOM, Figure S1). The local impasse optima are therefore not limited to round list prices and/or round first offers. A locally weighted regression (LOWESS) of impasse risk on first-offer magnitude quantified the distance between the actual data and the locally weighted regression curve and confirmed substantial deviations (Table S5; OSF). This also allowed us to analytically establish three distinct impasse risk zones: a safety zone consisting of buyers' offers above 90% of the list price, an acceleration zone with multiple drops in impasse risk including first offers from 90% to 20% of the list price, and a saturation zone consisting of buyers' offers below 20% of the list price (Figure 1; OSF). We will return to this finding in the Discussion.

3.5. Moderation by Price Certainty and Product Demand

3.5.1. Moderation by Price Certainty. Price certainty did not moderate the relationship between first-offer magnitude and final prices (Figure S2 in SOM). The linear regression coefficients were nearly identical ($Z \leq 1.14$, $p \geq .25$; see Table S6). However, price certainty did moderate the relationship between first-offer magnitude and impasse risk: for high certainty, a quadratic model provided the best fit ($R^2 = .968$), whereas the relationship remained quartic for medium ($R^2 = .992$) and low price certainty ($R^2 = .993$; Table S7, Figure S2b). The absolute level of impasse risk was higher for medium compared to low price certainty (Figure S2, green lines), and regression coefficients differed significantly ($Z \leq 3.12$, $p \geq .002$ for the quadratic term; all other comparisons $Z \leq 1.84$, $p \geq .066$). We return to these findings in the Discussion.

3.5.2. Moderation by Product Demand. Product demand from other interested buyers moderated the relationships between first-offer magnitude and (1) final prices as well as (2) impasse risk. The relationship between buyers' first-offer magnitude and final price was adequately explained by linear regressions without polynomials (Table S8). However, price certainty moderated this linear relationship, as the regression coefficients differed significantly between all demand levels ($Z \geq 2.11$, $p \leq .035$). The lower the product demand, the steeper the linear regression slopes, suggesting stronger anchoring effects (Figure S3b, SOM).

Second, the relationship between first-offer magnitude and impasse risk was also moderated by product demand, as the regression coefficients differed between all conditions ($Z \geq 4.09$, $p \leq .001$; Figure S3). The absolute level of impasse risk was higher when product demand was high compared to medium and low. The impasse risk functions were also moderated. A cubic model provided the best fit for low ($R^2 = .992$) and high demand ($R^2 = .978$), whereas a quartic model provided the best fit for medium demand ($R^2 = .987$; see Table S9, Figure S3b). We return to these moderation effects in the Discussion.

4. Discussion

We leveraged sales negotiation field data to understand the first-offer conundrum. Specifically, we integrated two previously separate literature streams and quantified both the impasse risk and the anchoring benefits on final prices across the entire first-offer spectrum (Figure 1). We also identified the ideal first-offer value for which both the impasse risk and final price are minimal. Buyers on eBay who place an equal value on a low final price and on avoiding an impasse should make a first offer at 80% of the sellers' initial list price (SOM for analytical details). This recommended "ideal" first offer minimizes both the impasse risk and final price paid and differs across product categories: e.g., in the art category it is 75% of the list price, but for music it is 65%. The recommended first offer also depends on how much buyers want to avoid an impasse versus achieve a low final price. Negotiators on eBay who seek to minimize impasse risk should open with 90% of the list price (i.e., point of minimal impasse risk in Figure 1). Counterintuitively, this impasse risk is even lower than that for first offers from 91% to >99.5%—this is reflected in the nonlinear, quartic function (safety zone). However, negotiators who prioritize price over impasse risk should open with 5% of the list price (i.e., lowest final price in Figure 1; Table S10). Negotiators who want to avoid an impasse altogether (for example, because they value the product more than what it is listed for) can just pay the full list price immediately and thereby avoid a negotiation and minimize the impasse risk. Our recommendation to offer 90% of the list price does not apply to these buyers who value the product much more than the list price and therefore decide not to negotiate.

4.1. Theoretical and Empirical Contributions

4.1.1. Linearity and Nonlinearity for First-Offer Anchoring and Impasse Risk. To our knowledge, no prior studies have empirically examined the prominent linearity assumptions regarding how increasingly assertive offers (1) anchor final prices and (2) increase impasse risk. Prior studies (Jang et al. 2018) employ constrained study designs lacking sufficient granularity of first-offer magnitude[2] and frequently employ non-incentivized, simulated negotiation scenarios with limited ecological validity. Typically, such research designs examined one moderate and one extreme first offer (left- and right-hand sides of the x-axis in Figure 1) and interpreted the higher impasse risk of more assertive offers as empirical evidence for a linear relationship between offer magnitude and impasse risk. Our paper offers novel insights into the nature of anchoring and impasse effects at a fine-grained level across the entire spectrum of first-offer magnitude.

Although the anchoring effect flattens out beyond certain thresholds in cognitive evaluation tasks (Chapman and Johnson 1994), anchoring effects on final prices reveal a strictly linear function that holds across the entire range of first-offer magnitude, from very moderate to very assertive first offers. Anchoring effects do not asymptotically flatten out beyond a certain threshold (e.g. Hsee et al. 2005, Schultze and Loschelder 2021) but rather exert a fully linear effect in the present data—provided an agreement was reached. Conversely, the effect of first offers on impasse risk is nonlinear. Contrary to the linearity assumption predicted by expert scholars, our analysis establishes a quartic relationship between first-offer magnitude and impasse risk. This quartic function indicates three separate zones of distinct effects on impasses.

4.1.2. Three Impasse Risk Zones Across the Full Spectrum of First-Offer Magnitude. Figure 1 illustrates these three zones. The safety zone includes first offers between <100% and 90% of the seller's list price. Counterintuitively, the impasse risk is higher for first offers closer to the full list price (100%) than for slightly more assertive offers—that is, the quartic function decreases from 100% to 90%. Buyers who want to negotiate and avoid an impasse should therefore not offer more than 90% of the list price; ironically, they end up paying more and are more likely to cause an impasse than negotiators who offer only 90% of the list price (i.e., the impasse optimum). It is possible that sellers who are offered (almost) their full list price regret having their first offer accepted (Galinsky et al. 2002), re-assess the true value of their product, seek an impasse, and subsequently relist at a higher price. Sellers may also be offended by buyers seeking to negotiate only a few percent off the list price—say, between \$1 and \$9 for a product listed for \$100.

The subsequent acceleration zone includes offers between 90%–20% of list prices. A visual inspection reveals two distinct patterns: first, the impasse risk linearly increases as first offers become

[2] Northcraft and Neale (1987) varied first-offer magnitude across four different anchor levels (rather than the more common two levels), but did not examine or find any nonlinear effects for these four levels.

more assertive. Second, this linear increase is punctuated by salient points of offer magnitude at which the impasse risk drops locally (i.e., local optima). For example, buyers who offer 50% of the list price have a lower impasse risk than buyers who offer slightly more (i.e., 51%) or slightly less (49%). These drops are statistically identifiable through quantifying the deviation of data points from the LOWESS curve. Using median absolute deviation as a criterion, we identified the ten biggest drops below the quartic function at 60%, 50%, 80%, 75%, 67%, 70%, 40%, 83%, 33%, and 63% (Table S5). These local optima occur at cognitively salient points for which fractions can be easily calculated (Braithwaite and Siegler 2018) and so which are mentally easy to process: 67% constitutes two thirds of the list price—for instance, a \$100 offer for a product listed at \$150. These easily calculated offers may foster more acceptance (see Yan and Pena-Marin 2017). In contrast, more precise offers may seem more competently calculated (e.g., Loschelder et al. 2016) but may also make the offer-maker seem more inflexible (e.g., Lee et al. 2018), thereby increasing the impasse risk compared to round, easily processed offers.

Finally, the saturation zone includes very assertive first offers at less than 20% of the seller's list price. The impasse curve flattens in this zone, indicating a relatively stable and high impasse risk (around 95% of all negotiations in this zone end in an impasse), irrespective of whether buyers offer 15% or only 1% of the list price. In contrast, final prices—provided the offer is accepted—continue to decrease linearly as first offers become more assertive. Negotiators who are unconcerned about an impasse can benefit from this and make more assertive first offers below 20% of the list price to minimize final prices at a relatively stable impasse risk.

4.1.3. Moderation by Price Certainty and Product Demand. Price certainty and buyer demand moderates these effects, and thereby extend our understanding of the (non)linearity assumptions. While price certainty does not moderate the linear effect of offer magnitude on final prices, the impasse risk increases when price certainty is high, and buyers and sellers are confident about a product's objective value (Figure S2, green lines). Crucially, price certainty also moderates the impasse risk functions (Figure S2b). For high price certainty, impasse risk increases from the very beginning (i.e., no safety zone), while quartic functions for medium and low price certainty show that the impasse risk increases for offers below about 90% of the list price (i.e., transition from safety to acceleration zone).

Buyer demand moderates both anchoring and impasse risk effects (Figure S3b). The linear anchoring function is steeper and more pronounced for low compared to medium and high demand (blue functions). Similar to price certainty, the impasse risk increases much earlier when buyer demand was high, while for medium (low) demand, the impasse risk only increases for offers below 90% (85%) of the list price.

4.2. Methodological Contributions

This study's novel theoretical and empirical insights are made possible by methodological innovations: first, we analyze a large-scale, real-world data set. We hope to encourage other scholars in management to also use real-world negotiation data (Jang et al. 2018). Scholars often incorrectly assume that relationships with industry or government are necessary to obtain real-world data, but generous scholars such as Backus et al. (2020) increasingly share sophisticated data sets on various topics, from the influence of politics in psychological research (Viganola et al. 2018) to marathon running (Allen et al. 2017). Second, we use both traditional and advanced machine learning algorithms to analyze this data. To help scholars pursue comparable research, we are also sharing extensive documentation, instructions, and code on how to analyze this data using SQL, Python, and machine learning algorithms (OSF).

4.3. Applied Contributions

Negotiators everywhere ask themselves how high their first offer should be, but this question has remained unanswered. Osório (2020) 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 (Galinsky and Mussweiler 2001, Loschelder et al. 2016), yet they do not know how high the offer should be. Advice is often based on vague, imprecise, confusing or even conflicting anecdotal guidance (Table S1). In addition, negotiators underestimate the size of the bargaining zone (Larrick and Wu 2007), and their first offers are often not ambitious enough. Our paper provides empirical insights across the entire, continuous spectrum of offer magnitude and establishes linear anchoring and nonlinear, quartic impasse effects across over 30 different product categories in our sales negotiation data.

To help negotiators use this knowledge, we offer two types of free advice on how high the first offer should be, depending on individual variables (https://firstofferadvice.com/advice). Negotiators choose product type and list price, and how willing they are to risk an impasse. Our calculator helps them determine the ideal first-offer magnitude based on our analyses of more than 25 million negotiations. In addition to this calculator, our offer table illustrates how the recommended first offer changes across increasing levels of price uncertainty and willingness to risk an impasse. Figure 3 shows this for a given list price of \$500. For example, a negotiator interested in an art piece listed at \$500 and willing to accept up to 60% impasse risk should make a first offer of \$225. Visitors to our website can consult an online version of this table to any list price they're interested in (https://firstofferadvice.com/advice).

Impasse Risk

Price Uncertainty

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

Figure 3 First-Offer Recommendations as a Function of Increasing Price Uncertainty and Buyers' Impasse Risk Sensitivity.

4.4. Limitations and Avenues for Future Work

This research is not without limitations. Analyzing real-world data allowed us to identify both the linear anchoring and the nonlinear, quartic impasse effects of first offers. Inevitably, these data do not allow experimental manipulation of factors to causally probe the underlying mechanisms for these relationships. For example, the drop in impasse risks at salient points (Figure 1) could be related to the mental ease with which offer magnitudes can be calculated. Future work could experimentally manipulate both mental load and offer magnitude to control the ease with which such offers can be mentally calculated and evaluated (see Yan and Pena-Marin 2017, Lee et al. 2018). Future studies could also test whether interventions can widen the range of these points across the full offer spectrum. For example, the drop in impasse risk around the 50% mark could be widened to 45% to 55% by making range offers (Ames and Mason 2015), providing rationales (Lee and Ames 2017), or utilizing first-offer framing effects (Majer et al. 2020). Negotiators can also strategically adapt their communication style (Jeong et al. 2019) or communicate emotions as social information (van Kleef 2016, van Kleef and Côté 2018) when negotiating. Another intervention could test whether a simple verbal description of the fraction lowers the impasse risk (e.g., "*I'm offering $30, that's about one third of your $100 list price*") compared to only stating the offer ("*I'm offering $30*").

The relationship between first offers and impasses is likely different for services (Hart and Schweitzer 2020). Only two of the 34 categories in our data set included services (i.e., specialty services, business and industrial). There are numerous other negotiations that are structurally different from a marketplace setting, such as face-to-face negotiations over cars (Chandra et al. 2017), real estate (Lee et al. 2018), or salary negotiations (Pinkley and Northcraft 2000). These could feature different "ideal" first-offer magnitudes and possibly different patterns of (non)linearity. Future research should examine the impasse and anchoring effects in other real-world settings.

Future research should also study buyer bias (Figure 2). One plausible explanation for the bias is that, in our data, sellers' list prices are further removed from their reservation prices (RPs) than buyers' first offers are from their RPs, which has the effect that the seller must concede more than the buyer to reach an agreement. Imagine a negotiation between a seller whose list price is \$140 and whose RP is \$100 (Δ = \$40) and a buyer whose first offer is \$90 and whose RP is \$110 (Δ = \$20). Blount and colleagues describe this as an *asymmetric opening offer zone* because sellers are farther removed from their RP than buyers are (Blount 2000, Blount et al. 1996, Blount White and Neale 1994). The seller here must concede at least \$30, but the buyer only must concede \$10 to reach an agreement. Future research with data including information about negotiators' RPs (which the present data set unfortunately lacks) should examine this possibility that asymmetric opening offer zones cause the observed buyer bias.

Future research could also assess the relative importance of aspiration prices and RPs for negotiators' first-offer assertiveness. While both higher aspirations and RPs increase first-offer assertiveness (Blount White and Neale 1994), future research should expand our understanding about their relative impact on buyers' and sellers' (distinct) first-offer assertiveness. Especially for our marketplace data, it is possible that RPs are relatively less influential for first-offer assertiveness than aspiration points (Blount et al. 1996)—particularly for sellers. If sellers' first-offer assertiveness is indeed more strongly impacted by aspirations, whereas buyers are more strongly impacted by RPs, this would explain the asymmetric opening offer zone and resultant buyer bias.

Finally, certain offers are easier to locate and process numerically within the opening offer zone than others. The local impasse optima (Figure 1) may emerge because they constitute salient fractions of the list price (e.g., 75%, 50%, or 20%) that are intuitively easier to calculate than offers of, for example, 74%, 48%, or 17% (Braithwaite and Siegler 2018). Easily locating buyer offers in the opening offer zone could allow sellers to quickly identify the magnitude of buyers' concessions. For example, if a seller lists at \$100 and has an RP of \$60, a buyer's first offer of \$80 is easily processed as 33% higher than the \$60 RP (and 80% of the list price). In contrast, offers of \$82, \$57, or \$73 may be more difficult to process numerically, making it cognitively harder for the seller to identify the magnitude of the buyer's concessions.

5. Conclusion

We integrate previously separate literatures on first-offer anchoring and impasses and draw on a large-scale, real-world data set of incentivized negotiations to establish a linear anchoring and a nonlinear, quartic impasse effect for first-offer magnitude. Price certainty and buyer demand moderate these findings and (non)linearity functions. Finally, we offer evidence-based advice to help negotiation practitioners solve the first-offer conundrum in their specific negotiation situations.

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