Do Consumers Expect Values to Increase Or Decrease Over Time?

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[to cite]:

[url]:
http://www.acrwebsite.org/volumes/1700106/volumes/v11e/E-11

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Paper #1: Smaller Numerical Differences can Enhance Product Appeal
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Paper #2: Do Consumers Expect Values to Increase or Decrease over Time?
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Paper #3: Holistic Processing and Left-Digit Effect
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Paper #4: Not Just a Number: The Effect of 100% Claims on Consumers
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Smaller Numerical Differences can Enhance Product Appeal
EXTENDED ABSTRACT
We demonstrate that smaller numerical differences can be perceptually larger, enhancing product appeal. When a change in a product’s numerical information is decimal-to-integer (3.4 to 4) rather than integer-to-integer (3 to 4), consumers infer that intermediate values were skipped, moving the product into a different category and increasing product attractiveness.

This research explores situations in which smaller numerical differences can be perceptually larger. We find that when a product’s numerical information changes from a decimal number to the next integer (e.g., 5.4 to 6), consumers are likely to find the product more appealing than when the change is between two consecutive integers (e.g., from 5 to 6), even though the second difference is mathematically larger. We propose that when a product’s version number or rating changes from a decimal number to an integer, consumers infer that the product has skipped over intermediate values and crossed the threshold into a new category, which indicates greater improvement.

Specifically, when consumers encounter a decimal number, they may infer that it is drawn from a relatively precise numerical scale. Distances between units on more precise scales can be perceptually greater, and may suggest that there are intermediate values (e.g., Pandaleaere, Briers and Lernmbregs 2011; Zhang and Schwarz 2012). If decimal numbers are perceived as intermediate values, integers could then become endpoints or category boundaries. Building on research showing the impact of category boundaries on consumers’ perceptions and behavior (e.g., Irmak, Walker-Naylor, and Bearden 2011; Isaac and Schindler 2013), we suggest that a decimal-to-integer change is perceived as boundary crossing. Consumers should therefore conclude that the product has improved substantively, making it more appealing. If the change is from one integer to the next, consumers have no reason to assume that intermediate values exist; so an integer-to-integer difference will be perceived as more sequential.

The decimal-to-integer effect is contingent on the perception that a category boundary has been crossed. It should not occur for changes within the same integer (e.g., from 2 to 2.6), as there is no integer boundary. If the decimal number is close to the integer (e.g., 2.8 vs. 3), the difference may be too small for the integer to be a meaningful category boundary, which should also eliminate the effect.

Because the decimal-to-integer effect derives from the perception that intermediate numerical values have been skipped, information about the nature of the scale should moderate the effect. Explicit information indicating that there are intermediate (decimal) values should make integer-to-integer changes more meaningful, but should not affect the perception of decimal-to-integer changes. Because integer-to-integer changes would then skip over more intermediate values, the effect should be reversed. In three studies, we provide support for the proposed effect and its underlying process.

Study 1 demonstrated that a decimal-to-integer change in product version numbers can increase perceived product attractiveness. We randomly assigned undergraduate participants (n=96) to one of two conditions: software whose existing version number was either 3.4 to 3.4. The new version in both conditions was 4. Participants who were told that the upgrade under consideration was from version 3.4 to version 4 were more favorable about an upgrade than those who were told that the upgrade being considered was from version 3 to version 4 (t(94)=2.16, p=.03).

In study 2, participants (n=387) read about two different software versions or two different camera models, with different combinations of version/model numbers. The pattern of results was similar for both products, and the data was combined for the analysis. The difference in version numbers had a significant effect on participants’ interest in the product (F(4, 377) = 4.07, p = .003). Post-hoc analyses revealed that interest in the product was lower in the 2 vs. 3 condition (M = 4.68, SD = 1.79) compared with the 2.4 vs. 3 condition (M = 5.61, SD = 1.14, p < .001) and compared with a 2.7 to 3.3 change (M = 5.33, SD = 1.55; p = .02). There was no significant difference between the 2 vs. 3 condition and the 2 vs. 2.6 condition (M = 5.00, SD = 1.64; p = .62) and the 2.8 vs. 3 condition (M = 5.14, SD = 1.55; p = .20). These results indicate that the effect is driven by the combination of numerical precision and the crossing of a numerical category boundary.

In study 3, we explored the moderating role of explicit cues regarding scale precision. Explicit information about scale precision should indicate that integer-to-integer changes have also skipped over intermediate values, making them seem boundary crossing; because they skip over more intermediate values than decimal-to-integer changes, the effect should be reversed. We also measured the mediating role of perceived category change in driving the effect. Participants (N=190) read about a camera whose “color accuracy rating” had improved from 5 to 6 (integer condition) or from 5.4 to 6 (decimal condition). They were provided a scale illustration that included only integer values (round scale) or one that also included intermediate decimal values (precise scale).

A 2 × 2 ANOVA revealed a significant interaction (F(1, 186) = 9.42, p < .001). In the round scale condition, the camera was evaluated more positively when the color accuracy improved from 5.4 to 6 (M = 5.78, SD = .90) as opposed to an improvement from 5 to 6 (M = 5.35, SD = .82; F(1, 186) = 5.32, p = .02). In the precise scale condition, the camera was evaluated more positively in the integer condition (M = 6.06, SD = .70) compared to the decimal condition (M = 5.59, SD = .97; F(1, 186) = 7.96, p = .005). As expected, perception of category change mediated the effect, such that the mediation was...
Do Consumers Expect Values to Increase or Decrease over Time?

EXTENDED ABSTRACT

We show that people associate quantity changes with increases—when shown one data point (e.g., this year’s profit) and asked to estimate next year’s profit, consumers expect the estimate to be higher. We report findings from five studies and contribute to the forecasting literature.

Do we expect a company’s profits to be higher or lower next year over this year? Likewise, will companies advertise more next year versus this year? Why? Consider profits. A priori there is no reason to expect profits to increase or decrease next year—some companies do better than others. However, we suggest that consumers’ expectations vary systematically—given profits this year, consumers expect profits next year to be higher. This occurs because consumers associate change with increase (rather than with decrease).

Is this normative? Imagine estimating the number of trees cut each year in the rain forest. We suggest that irrespective of negative framing—number of trees cut—or positive—the number of trees saved, people expect increases next (vs. this) year. This also rules out optimism bias (Weinstein 1980) as an explanation because optimism would lead to a lower estimate in the negative condition.

Our theory is related to, yet different from research on trend forecasting. For example, Harvey and Bolger (1996) suggest that consumers expect trends to continue. Relatedly, Thomson and colleagues (2013) find that, people are better at generating forecasts for, and at identifying ascending, rather than descending, trends. This occurs because people are more often exposed to increasing (vs. decreasing) data series (Harvey and Bolger 1996).

We make a broader point: even when consumers have only one data point (and not a trend), they expect the next point to be higher. These effects emerge because of learned association—because consumers encounter increasing (vs. decreasing) trends more often, they believe change implies increase. Indeed, physical changes in everyday life are associated with increases—saplings grow into trees, cubs become tigers, and children, adults. Abstract changes also lead to increases—trees grow stronger and tigers more ferocious. Thus, we believe that people tend to generate increasing estimates because they naturally expect quantifiable events to improve over time. Taken together, we predict change is associated with increase and demonstrate this in five studies.

If change is associated with increases because of learned association, then people should generate more examples of events leading to increases, than to decreases or remain unchanged. In a pilot study using a 3-cell design (N=127), participants listed as many things as they could think of that increased, decreased, or did not change in their life. As expected, the number of examples in the increase (vs. decrease or no-change) condition was higher (Mincrease = 5.02, Mdecrease = 4.38, Mno change = 3.63, F(3, 123) = 10.57, p < .001). Thus, people are able to remember positive (vs. negative) changes more.

In study 1, we demonstrate our basic effect—even when provided with only one data point, people predict increases. We used a 2 timeframe (near vs. far) by 6 replicates design (N=501). Each replicate included a brief introduction and a benchmark value. For example, in the rainforest scenario, we indicated that in 2010, 113,000 square miles of rainforest were cut; we then asked participants to estimate the amount cut in 2012 (near) or in 2015 (far). As predicted, in each replicate, participants expected the estimates to be higher than the benchmark for both near and far conditions. Furthermore, consistent with the belief that change is associated with increases, the estimate was higher in the far (vs. near) condition. Participants also indicated what they thought while providing estimates. Thought protocol analyses suggest that they thought more about increases (vs. decreases or status quo) in all the conditions, thus confirming our intuition that change is associated with increase.

In study 2, using three replicate scenarios from study 1, we manipulated frame to be positive or negative (N=62). For instance, in the rainforest scenario, participants in the positive (negative) frame read about the number of trees saved (cut) in the rainforest and provided an estimate for next year. Both estimates were higher than the benchmark (ps < .05), ruling out optimism as an explanation. To wit, participants estimated in the negative frame that the numbers of trees cut would increase but also estimated in the positive frame that the number of trees saved would increase, even if it is logically impossible for both to increase.

In study 3 (N=97), participants imagined searching for a new AC unit to buy. They were told that the company would be making changes to the AC efficiency level or price depending on condition, and were subsequently asked whether they would buy the AC at that moment or wait. If consumers predict both favorable and unfavorable attributes to increase over time, this might lead to different buying decisions depending on the focal attribute. As predicted, participants in price condition were more likely to buy the product sooner for fear that the price would increase (Mprice = 4.81) than participants in efficiency condition, who hoped the efficiency would increase (Mefficiency = 3.47; F(1, 95) = 22.40, p < 0.001).

If the association between change and increase is learned, then participants should respond faster to changes that relate to increases (vs. decreases). We measured response latencies in study 4 to provide such evidence. Participants read one of three scenarios, and were provided a benchmark value (e.g., number of visits to the ER made this month; N=115). Following this value, we presented them with 60 potential future estimates (e.g., ER visit next month). In each case, participants assessed if this estimate was likely to be correct or not. As predicted, with an increase (vs. a decrease), participants deemed the change more likely and also responded faster.

Together, we show that changes are associated with increases. Thus, we generalize the research on trends by showing that even when only one data point exists, consumers expect increases (vs. decreases). However, contrary to this research, which suggests that consumers expect both increasing and decreasing trends to continue, when only one value is presented, the estimate is higher. We believe these finding are likely to impact not only numerous marketing contexts (e.g., cost, efficiency, performance expectations) but also provides important insight into how people evaluate numbers.

Holistic Processing and Left-Digit Effect

EXTENDED ABSTRACT

The paper examines when people are more likely to fall prey to the left-digit effect. We show that when people make stimulus-based (vs. memory-based) evaluations, the left-digit effect is enhanced. We
argue that this effect is driven by the relative salience of digital (vs. holistic) processing of price information.

This paper focuses on a well-documented and one of the most pervasive biases in behavioral pricing known as the left-digit effect (Manning and Sprott 2009; Thomas and Morwitz 2005). The effect manifests as individuals’ tendency to anchor their judgments of numeric differences on left-most digits. Falling prey to the left-digit bias, people judge the difference between $8.00 and $6.99 ($=1.01) to be larger than that between $8.01 and $7.00 (=$1.01). While its robustness and implications have been demonstrated in a variety of contexts, the conditions that facilitate the left-digit effect remain unclear.

Building on the behavioral pricing literature (Cheng and Monroe 2013; Monroe and Lee 1999; Vanhuele and Dreze 2002) and the cognitive psychology literature (Thvenot and Barouillet 2006), we propose that people compare prices in two ways: by comparing them digit-by-digit under digital processing and by estimating approximate price differences under holistic processing. When people compare prices (e.g. $8.00 and $6.99) digitally (i.e. as digit sequences – 8-0-0 and 6-9-9), they are more likely to exhibit the left-digit effect. When they compare prices holistically (i.e. as rough approximations ≈8 and ≈7), the left-digit effect is reduced. We argue and show empirically that reference price type (stimulus-based vs. memory-based) drives price processing (digital vs. holistic) and, consequently, affects the magnitude of the left-digit effect. When people rely on stimulus-based (memory-based) reference prices, they are more likely to rely on digital (holistic) price processing and are more (less) susceptible to the left-digit effect.

Study 1 tested our predictions using supermarket scanner data. We inferred reference price type from product category usage: infrequent (vs. frequent) category users were assumed to rely more on stimulus-based (vs. memory-based) reference prices (Kyung and Thomas 2016; Rajendran and Tellis 1994). Thus, infrequent (vs. frequent) category users were expected to be more susceptible to the left-digit effect. Analysis of choice data supported our predictions.

Study 2 manipulated reference price type in a controlled experiment. The study employed a 2 (left-digit difference: small vs. large) x 2 (reference price: stimulus-based vs. memory-based) between-subjects design (n=145). Participants rated pairs of premium brand and store brand prices, four fillers and one test pair. Test pair prices were $4.01 vs. $3.00 ($4.00 vs. $2.99) in the small (large) left-digit difference condition. Participants saw premium and store brand prices (e.g. $8.00 and $6.99) digitally (i.e. as digit sequences – 8-0-0 and 6-9-9), they are more likely to exhibit the left-digit effect. When people compare prices holistically (i.e. as rough approximations ≈8 and ≈7), the left-digit effect is reduced. We argue and show empirically that reference price type (stimulus-based vs. memory-based) drives price processing (digital vs. holistic) and, consequently, affects the magnitude of the left-digit effect. When people rely on stimulus-based (memory-based) reference prices, they are more likely to rely on digital (holistic) price processing and are more (less) susceptible to the left-digit effect.

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We found a marginal effect of left-digit difference (F(1,141)=3.26, p=.073), and an interaction between left-digit difference and reference price (F(1,141)=4.84, p=.029). The effect of left-digit difference was significant in the stimulus-based condition (MSmall LDD=3.43 vs. Mlarge LDD=2.58, F(1,141)=8.08, p<.005). The effect was not significant in the memory-based condition (MSmall LDD=2.83 vs. Mlarge LDD=2.92, F<1). Consistent with our predictions, the left-digit effect was stronger when people relied on stimulus-based (vs. memory-based) reference prices.

Studies 3 and 4 ruled out alternative process accounts of the interaction between left-digit difference and reference price. One could argue that memory-based reference prices reduced the left-digit effect not because people relied more on holistic processing, but because they were less certain of their price attitudes and gave less extreme price evaluations to small and large left-digit difference pairs. To rule out this account we introduced a numeric price difference manipulation in studies 3 and 4. If attitude certainty was driving the effect of reference price type on the left-digit effect, there would be a stronger effect of left-digit difference and a stronger effect of objective numeric difference in the stimulus-based (vs. memory-based) condition.

Study 3 employed a 2 (left-digit difference: small vs. large; within-subjects) x 2 (reference price: stimulus-based vs. memory-based; between-subjects) x 6 (numeric difference: $1.01 to $7.01, 6 levels; within-subjects) mixed factorial design (n=120*2*6=1440). Counter to the attitude certainty account, we found an interaction between left-digit difference and reference price (F(1,118)=3.86, p=.05), but no interaction between numeric price difference and reference price (F<1). The left-digit effect was stronger in stimulus-based evaluations (MSmall LDD=6.19 vs. Mlarge LDD=6.71, F(1,118)=31.14, p<.001), than in memory-based evaluations (MSmall LDD=6.22 vs. Mlarge LDD=6.48, F(1,118)=7.09, p<.01).

Studies 2 and 3 used 99-ending (00-ending) prices for low (high) left-digit prices. One could argue that more cognitively taxing memory-based comparisons made people less likely to infer that 99-endings prices were low or “special” prices (Anderson and Simester 2003; Rottenstreich, Sood, and Brenner 2007; Schindler 1991). To rule out this account we tested the effect of reference price type for both 99 and 75-ending prices. If inference-making was driving the results we would expect to replicate our results for 99, but not 75-ending prices.

Study 4 employed a 2 (left-digit difference: small vs. large; between-subjects) x 2 (reference price: stimulus-based vs. memory-based; between-subjects) x 3 (numeric difference: 3 levels; within-subjects) x 2 (endings: 99 vs. 75; within-subjects) mixed factorial design (n=99*2*3*2=1188). Counter to the inference-making account, we found an interaction between left-digit difference and reference price type (F(1,97)=5.00, p=.05), but no three-way interaction between left digits, reference price, and endings. The left-digit effect was stronger in stimulus-based evaluations (MSmall LDD=5.99 vs. Mlarge LDD=6.73, F(1,97)=80.99, p<.001), than in memory-based evaluations (MSmall LDD=5.90 vs. Mlarge LDD=6.39, F(1,97)=40.70, p<.001). The results also countered the attitude certainty account.

Study 5 (n=245) directly tested our process account. It examined the effect of number of evaluations (multiple vs. single) – a factor linked to piecemeal/holistic processing (Hochstein and Ahissar 2002; Jia, Shiv, and Rao 2014). Building on the finding that people focus more on gestalt-oriented (piecemeal) features in single (multiple) viewings, we predicted that single stimulus-based price comparisons would be similar to memory-based price comparisons. Indeed, the left-digit effect was significant in the multiple stimulus-based comparison condition (MSmall LDD=2.18 vs. Mlarge LDD=3.34, F(1,225)=7.52, p=.007), but not in the single stimulus-based evaluation condition, nor in the memory-based condition. Consistent with the digital/holistic framework multiple stimulus-based (vs. single stimulus-based and multiple memory-based) comparisons, those expected to rely more on holistic (vs. digital) processing, produced a stronger left-digit effect.

We outline a digital/holistic framework of price comparisons and identify reference price type as a factor that determines whether and when the left-digit effect will emerge.

**Not Just a Number:**

**The Effect of 100% Claims on Consumers**

**EXTENDED ABSTRACT**

We find that participants evaluate products less favorably when those products carry a pseudo-informative 100% claim (e.g., “100% juice”), as compared with a 99% or non-numerical claim, or even a
101% claim. This effect is triggered by enhanced focus on the symbol of “100%” and decreased reliance on numerical information.

Many product labels include numerical claims. Consumers interpret these claims in different ways, beyond their numerical value. Non-round numbers, for example, are considered more informative and scientific than round numbers (Guang-Xie and Kronrod 2012). Correspondingly, evaluations of products associated with non-round numbers are based more on cognitions, whereas evaluations of products associated with round numbers lean more on feelings (Wadhwa and Zhang 2015). Round numbers, on the other hand, symbolize completion, and consumers are therefore more willing to accept offers with round prices (Yan and Pena-Marín 2017).

In the current research we focus on a common yet unexplored numerical claim, a 100% claim (e.g., “100% natural”). More than any other round number, 100% mathematically denotes completeness, and accordingly, in everyday language, the term “100%” stands for completeness, fullness or perfection (Lee 2014). Thus, it is not surprising that marketers intuitively believe that a 100% claim can make products more appealing, an intuition reflected in their extensive use of such claims. Indeed, Canadian consumers perceive a “100% Canadian milk” claim on milk and ice cream as an indication of product quality (Forbes-Brown, Micheels, and Hobbs 2016).

We suggest that this intuition may backfire when the 100% claim is pseudo-informative, namely, does not convey meaningful information regarding the associated product—for example, a claim stating that a drink contains “100% juice”, which does not specify percentages of fruit content or other similar information. In these cases, consumers may rely less on the numerical information conveyed by the claim, and refer more to its symbolism. In addition, because the perfection symbolized by the term “100%” might be perceived as “cheap talk” that cannot actually be measured, consumer’s product evaluations decrease.

Four experiments show that participants evaluate products less favorably when those products carry a pseudo-informative 100% claim, as compared with a 99%, non-numerical, and even 101% claim (that serves as a symbol). We further show that the effect of a pseudo-informative 100% claim is triggered by perceptions of low measurability of the information embedded in the claim, suggesting an enhanced focus on 100% as a symbol.

Study 1 tested the effect of a pseudo-informative 100% claim on evaluations. Participants (n=99) reviewed a picture of a beverage with a label that contained either a “100% juice” or a “99% juice” claim. They provided product evaluations by indicating on 7-point scales how appealing, tasty, healthy, fresh, natural, good versus bad, of high versus low quality, and close to perfection this product seemed to them (Cronbach’s a=.89). Participants also reported their perceptions of the products consumers: how successful, powerful, and high versus low in status they perceived them to be (Cronbach’s a=.89). As expected, when the label contained a 100% claim, product evaluations were lower (M=4.36, SD =1.17) than when the label contained a 99% claim (M=4.80, SD=1.07; F(1, 97)=3.86, p=.05), and perceptions of the products consumers were less favorable (M=3.76, SD=1.16 vs. M=4.19, SD=.97; F(1, 97)=3.93, p=.05). Thus, a product label containing a 100% claim can sometimes harm product evaluations.

Study 2 (n=153) compared the effect of a 100% claim not only to that of a 99% claim, but also to that of a non-numeric claim. To make sure the (uninformative) numbers on the label triggers our effect, we used a foreign product—a Russian jam, such that participants could only understand the numbers, but not the text, written on the label. Put differently, the text on the label was exaggeratedly uninformative for participants. A MANOVA revealed significant differences in product evaluations (F(2, 150)=4.30, p=.015) and perceptions of the product’s consumers (F(2, 150)=4.77, p=.01). Product evaluations were lower with a 100% claim (M=3.42, SD=1.16) than with either a 99% claim (M=4.06, SD=1.26, p=.02) or a non-numeric (non-understandable) claim (M=3.89, SD=.97, p=.11). Perceptions of the jam’s consumers were also less favorable with a 100% claim (M=3.02, SD=1.06) than with either a 99% claim (M=3.51, SD=1.16, p=.06) or a non-numeric claim (M=3.62, SD=.93, p=.01).

If the effect of a pseudo-informative 100% claim is indeed triggered by decreased consideration of the numerical value of 100%, and enhanced consideration of its symbolism, then our effect should emerge also when a 100% claim is compared to other, superior, claims involving percentages that are symbolic rather than numerically informative. Thus, Study 3 used a 101%-satisfaction claim. Note that while 101% has no numerical logic, a 101%-satisfaction claim may imply extra effort to satisfy consumers, which consumers may find more convincing. Participants (n=81) reviewed a hotel picture that contained either a 100% or 101% “satisfaction guarantee” claim. As expected, evaluations of the hotel were lower with a 100% claim (M=4.94, SD=0.91) than with a 101% claim (M=5.36, SD=0.84; F(1,79)=4.53, p=.04), and perceptions of the hotel’s consumers were also less favorable (M=3.92, SD=1.10 vs. M=4.46, SD=1.17, F(1,79)=4.61, p=.035).

Study 4 aimed to provide more direct evidence for our hypothesis that consumers rely more heavily on the symbolism, rather than the numerical value, of a pseudo-informative 100% claim. Thus, Study 4 tested whether measurability perceptions mediate the claim effect on behavioral intentions (the mean of willingness to taste and willingness to buy the product, Cronbach’s a=.75). Participants (n=200) reviewed a picture of ice-bars that included one of three uninformative claims: Made with [100%/99%/no number mentioned] juice blend and other added ingredients. The results of a mediation analysis (PROCESS Model 4, multicategorical, with 5000 resamples; Hayes 2013) show that both the 99% claim and the non-numeric claim were perceived as more measurable than the 100% claim (B=.63, SE=.28, p=.03, 95% CI [.07,1.18] and B=.63, SE=.27, p=.025, 95% CI [.08,1.18], respectively). Importantly, the relative indirect effects of the difference between the 100% claim and both the 99% claim and the non-numeric claim on behavioral intentions through measurability were significant (B=.13, SE(boot)=.07, 95% CI [.02, .31] and B=.13, SE(boot)=.07, 95% CI [.02, .30], respectively), suggesting that the negative effect of a 100% claim on willingness to adopt the product ensues from perceptions of lower measurability of that claim.

Our results suggest that using 100% claims for products may sometimes have unintuitive effects on consumers, which may yield negative effects.

REFERENCES

Paper 1


1 Year Differs From 365 Days: A Conversational Logic
Analysis of Inferences From the Granularity of Quantitative

**Paper 2**
Harvey, Nigel, and Fergus Bolger (1996), “Graphs versus
Tables: Effects of Data Presentation Format on Judgmental
Forecasting,” International Journal of Forecasting 12 (1), 119-
137.
Events,” Journal of Personality and Social Psychology, 39 (5),
806.

**Paper 3**
Anderson, Eric T., and Duncan Simester (2003), “Effects of
$9 Price Endings on Retail Sales: Evidence from Field
Experiments,” Quantitative Marketing and Economics, 1 (1),
93-110.
of Behavioral Price Research (Part 1): Price as a Physical
Stimulus,” AMS review 3, (3), 103-29.
Hochstein, Shaul, and Merav Ahissar (2002), “View from the Top:
Hierarchies and Reverse Hierarchies in the Visual System,”
Neuron, 36 (5), 791-804.
Agnosia Effect: How More Visual Impressions Affect Product
Distinctiveness in Comparative Choice,” Journal of Consumer
Research, 41 (2), 342-360.
Disrupts Knowing: Blocking Implicit Price Memory,” Journal
of Marketing Research, 53, 937-53.
Manning, Kenneth C., and David E. Sprott (2009), “Price-Endings,
Left-Digit Effect and Choice,” Journal of Consumer Research,
36 (2), 328-335.
Monroe, Kent B, and Angela Y. Lee (1999), “Remembering Versus
Knowing: Issues in Buyers’ Processing of Price Information,”
Rajendran, K.L., and Gerald Tellis, (1994) “Contextual and
Temporal Components of Reference Price,” Journal of
Marketing, 58 (1), 22-34.
Rottenstreich, Yuval, Sanjay Sood, and Lyle Brenner, (2007),
“Feeling and Thinking in Memory-Based versus Stimulus-
Ending,” Advances in Consumer Research, 18, 794-801.
Numbers: Behavioral Evidence for Processing-Specific
Thomas, Manoj and Vicki G. Morwitz (2005), “Penny Wise and
Pound Foolish: The Left Digit Effect in Price Cognition,”
Journal of Consumer Research, 32 (1), 54-65.
Vanhuyle, Marc and Xavier Dréze (2002) “Measuring the
Price Knowledge Shoppers Bring to the Store,” Journal of
Marketing, 66, 72–85.

**Paper 4**
Bagchi, Rajesh And Xingbo Li (2011), “Illusionary Progress
in Loyalty Programs: Magnitudes, Reward Distances, and
Step-Size Ambiguity,” Journal of Consumer Research, 37 (5),
888-901.
Forbes-Brown, Shelicia, Eric T. Micheels, and Jill E. Hobbs (2016),
“Consumer Willingness to Pay for Dairy Products With the
100% Canadian Milk Label: A Discrete Choice Experiment,”
Journal of International Food & Agribusiness Marketing, 28
(3), 203-224.
Hayes, Andrew F. (2013), Introduction to Mediation, Moderation,
and Conditional Process Analysis. New York, NY: The
Guilford Press.
Approach to Numerical Perceptions,” unpublished dissertation,
Marketing Department, University of Oregon, Eugene, OR.
Lembregts, Christophe and Mario Pandelaere (2013), “Are All
Units Created Equal? The Effect of Default Units on Product
Evaluations,” Journal of Consumer Research, 39 (6), 1275-
1289.
of Time-Interval Descriptions on Goal-Pursuit Decisions,”
Journal of Marketing Research.
Shen, Luxi, and Oleg Urminsky (2013), “Making Sense of
Nonsense The Visual Salience of Units Determines Sensitivity
Thomson, Mary, Andrew Pollock, Sinan Gönil, and Dilek
Önkul (2013), “Effects of Trend Strength and Direction on
Performance and Consistency in Judgmental Exchange Rate
Forecasting,” International Journal of Forecasting, 29 (2),
337-353.
Ülkümen, Gülden, Manoj Thomas, and Vicki G. Morwitz (2008),
“Will I Spend More in 12 Months or a Year? The Effect of
Ease of Estimation and Confidence on Budget Estimates,”
Journal of Consumer Research, 35 (2), 245-256.
Wadhwa, Monica, and Kuangjie Zhang (2015), “This Number Just
Feels Right: The Impact of Roundedness of Price Numbers on
Product Evaluations,” Journal of Consumer Research, 41 (5),
1172-1185.
Yan, Dengfeng, and Jorge Pena-Marin (2017), “Round Off the
Bargaining: The Effects of Offer Roundness on Willingness to
Accept,” Journal of Consumer Research, 44 (2), 381-95.