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Trying Harder and Doing Worse: How Grocery Shoppers Track In-Store Spending

Although almost one in three U.S. households shops on a budget, it remains unclear whether and how shoppers track their in-store spending to stay within those budgets. A field study and two laboratory studies offer four key generalizations about budget shoppers in grocery stores: (1) They predominantly use mental computation strategies to track their in-store spending, (2) they adapt their mental computation strategy to the dominant range of price endings of items in their shopping baskets, (3) those who try to calculate the exact total price of their basket are less accurate than those who estimate the approximate price, and (4) motivated shoppers are less accurate than less motivated shoppers (because they tend to calculate rather than estimate the total basket price). A second field study demonstrates that shoppers who underestimate the total price of their basket are more likely to overspend, leading to negative store satisfaction.

Keywords: budget shoppers, in-store spending behavior, mental computation, basket estimation, retail price setting

One in seven U.S. households lives in poverty. Another one in six can afford only basic necessities, such as housing, food, and health care.[1] This state of affairs suggests that nearly one in three U.S. households must carefully plan its budgets and spend accordingly (Arends 2008).

Budget allocation and spending behavior models often implicitly assume that shoppers with budgets are knowledgeable about the total price of their shopping baskets as they shop (Bénabou and Tirole 2004; Ulkümen, Thomas, and Morwitz 2008). However, because shoppers' estimates of the prices of their shopping baskets mediate the relationship between budget allocation and actual in-store spending, it is critical to understand whether and how they estimate this total price. Inaccurate estimates could have notable implications for both consumer welfare (Heath and Soll 1996) and retail performance (Gómez, McLaughlin, and Wittink 2004).

Yet, despite the importance of understanding how shoppers on predetermined budgets might estimate the total price of their shopping baskets, it remains largely unclear whether, when, and how they keep track of in-store spending. This study has three objectives: (1) to determine whether and when budget shoppers keep track of how much they spend while shopping, (2) to understand how they estimate the total price of their shopping baskets, and (3) to examine the implications of estimation biases for consumer welfare and retail performance. We conduct this research in the context of grocery shopping, for which people shop multiple times per month and often spend 15%–20% of their income on ten or more items per trip (Bell and Lattin 1998).

We structure the remainder of this article as follows: First, after outlining existing research on budget allocations and spending behavior, we describe a field study in which we find that most budget shoppers track their in-store spending using various mental computation strategies. Second, the results of two lab experiments show that price endings, motivation, and estimation experience influence shoppers' ability to assess the total price of their shopping baskets accurately. Third, another field study reveals the implications of in-store estimates on spending behavior. Fourth, we discuss the implications of these findings for consumer welfare and retail performance and propose a future research agenda.

[1]In 2007, 37.3 million Americans (12.5%), or 17.9 million U.S. households (15.4%), lived in poverty (see www.census.gov). Another 19.9 million households earned enough to pass the poverty threshold but less than $32,250 per year, which equals the average amount Americans spend on food, housing, health care, and personal insurance and pensions.

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Shopping on a Budget

Budgeting, which we define as earmarking portions of income for specific uses, is common in many households and especially prevalent in lower-income households (Bénabou and Tirole 2004). To avoid financial distress, almost one in three U.S. households must carefully plan how to expend their income, though during recessions, this percentage increases considerably (see www.census.gov).

In both marketing and economics fields, descriptions of budget allocations and spending behavior tend to rely on a budget constraint utility model, in which consumers maximize their utility within their budget constraints (Hymans and Shapiro 1976; Kunreuther 1973). Budget allocation and spending behavior models often implicitly assume that budget shoppers know how much they spend while shopping (Du and Kamakura 2008; Frank, Douglas, and Polli 1967; Hauser and Urban 1986; Heath and Soll 1996; Ulkümen, Thomas, and Morwitz 2008). We propose that because the relationship between budget allocations and in-store spending is likely mediated by the shoppers' estimates of the total price of their shopping baskets, we need a better understanding of whether, when, and how budget shoppers keep track of their in-store spending, especially in the complex grocery shopping context.

Study 1: Do Budget Shoppers Track In-Store Spending?

To assess whether, when, and how budget shoppers may keep track of how much they spend while shopping, we conduct an exploratory field study with 293 shoppers, who we intercepted at the end of their shopping trip in one of two supermarkets located in Atlanta. Because budgeting is most prevalent among lower-income households, we selected one supermarket located in a zip code area with an average annual household income of \$22,540 (i.e., the poverty rate in the area is 35.7%) and another in a zip code area with an average annual household income that was more than twice as high, at \$46.478 (i.e., poverty rate = 14.3%).[2]

Method

At different periods during the week, one of four trained interviewers approached shoppers and asked them to participate in a five-minute, university-supported research study on shopping behavior. Respondents received a \$5 incentive for their participation.

In the first question, the interviewers asked participants whether they kept track of how much they spent while shopping for groceries. Respondents were then asked to describe when, why, and how they did so. After providing these open-ended responses, the respondents indicated how satisfied they would be with the store if they found out that they would have to pay more (less) than their estimated total (–5 = "very dissatisfied," and 5 = "very satisfied") and who they would hold most responsible (–5 = "myself," and 5 = "the store"). We also determined how often the respondents shopped for groceries per month and how much money they spent on average shopping trips. Finally, they indicated their age, sex, household size, and approximate monthly household income.

Two independent coders who were unaware of the research objectives classified and coded the open-ended responses, resolving any discrepancies through discussion. Across the open-ended questions, the agreement between the coders was generally high (Cohen's $\kappa > .80$, $p < .01$).

The average age of the participants was 41.3 years (range: 18–85 years), 50.2% were women, and their households contained an average of 2.8 people. Monthly household income averaged twice as low in the lower- compared with the higher-income area (\$1,823 versus \$3,789; $F(1, 232) = 39.83$, $p < .01$). Consistent with Engel's law, participants in the lower-income area spent a higher percentage of their income on groceries than their higher-income counterparts (20.9% versus 13.2%; $F(1, 219) = 17.91$, $p < .01$).

Results and Discussion

Do shoppers track in-store spending? Of the 293 participants, 84.6% claim to "at least sometimes" keep track of how much they are spending while shopping for groceries. Those who track in-store spending report doing so during an average of 7.4 (SD = 2.7) of 10 grocery shopping trips. Shoppers in the lower-income area are more likely to keep track than those in the higher-income area (89.7% versus 79.6%; $\chi^2 = 5.83$, $p < .05$).

Why and when do shoppers track in-store spending? As might be expected, the major reason respondents offer for tracking their in-store spending is budget constraint (87.6%). Of these, 36.3% always track their in-store spending, 36.7% primarily track when their total budget begins to run out (toward the end of the month), and 23.8% track during major shopping trips. Shoppers in the lower-income area are more likely either to always track in-store spending (38.7% versus 33.6%) or to track it when their total budget begins to run out (41.9% versus 31.0%), whereas those in higher-income areas are more likely to do so during major shopping trips (30.2% versus 17.7%; $\chi^2 = 8.54$, $p < .05$).

How do shoppers track in-store-spending? We identify three distinct tracking strategies: (1) mental computation (57.4%, "I add prices in my mind"), (2) calculators (26.4%, "I use a calculator"), and (3) shopping lists (14.5%, "I make a list before going to store"). Shoppers in the higher-income area are more likely to use mental computation strategies (66.4% versus 49.2%; $\chi^2 = 11.74$, $p < .01$). This finding may seem counterintuitive, but it reflects that shoppers in the lower-income area are more likely to use a calculator (35.2% versus 16.8%; $\chi^2 = 11.71$, $p < .01$). One in seven shoppers purchases what he or she absolutely needs, which entails the use of a shopping list.

[2]A comparison of the sales prices of 50 stockkeeping units (SKUs) from the most consumed product categories sold in both stores indicated that the stores charged comparable prices (see Appendix A). The average sales prices of the 50 SKUs do not differ (\$3.75 versus \$3.67; $t = 1.20$, $p > .10$), nor does the distribution of price endings ($\chi^2 = .10$, $p > .10$). Consistent with previous literature (Schindler 2006), the price endings predominantly (71.0%) range between \$.51 and \$.99 in both stores.

The most dominant of the tracking strategies is mental computation. More than 90% of those who rely on mental computation use a price-by-price approach; 45.2% round prices up ("I round all prices up to the dollar"), 24.0% round prices up and down to close denominations (e.g., $.00, $.10, and $.25; "I round to the closest $.10"), 14.4% add the exact price of each item ("Add each item as I put it in the cart"), and 11.5% round prices down ("I round prices down to a whole dollar amount").

Notable differences mark the two store locations (χ^2 = 14.03, $p < .05$). Shoppers in the lower-income area are more likely to add the exact prices of all items (20.9% versus 9.8%) and round prices to close denominations (32.6% versus 18.0%) than they are to round prices down (9.3% versus 13.1%) or up (30.2% versus 52.5%). These results suggest that shoppers in the lower-income area try harder to be more accurate.

Why do some shoppers never track in-store spending? Shoppers who claim that they never track their in-store spending also exhibit noteworthy differences depending on their income (χ^2 = 8.61, $p < .05$). Whereas shoppers in the higher-income area predominantly indicate that they do not track because they "don't have to" (52.0% versus 25.0%, "I don't have to budget. I make enough money"), their lower-income counterparts state that they do not track because they only buy absolute necessities (50.0% versus 32.0%, "I just shop for things I need and avoid things I don't").

Do estimation biases have implications? When shoppers must pay more than they expected, they tend to hold the retailer responsible (.9 > 0; t = 4.4, $p < .01$) and feel dissatisfied with the store (–1.1 < 0; t = 6.3, $p < .01$). However, when they pay less than expected, they attribute the benefit primarily to themselves (–1.2 < 0; t = 6.2, $p < .01$), and their store satisfaction remains neutral (+.3 ~ 0; t = 1.2, $p > .10$). These results, which are consistent across both store locations, confirm that estimation biases—especially underestimations that result in overspending—may have detrimental consequences for retailers.

The results of Study 1 demonstrate the relevance of in-store tracking. Many shoppers keep track of their spending while shopping for groceries. Some use calculators and shopping lists, but the most dominant strategy involves mental computation strategies. These results pose two questions: Why do consumers tend to round prices up, and why are shoppers in lower-income areas more likely than their higher-income counterparts to try to calculate basket prices using exact prices?

It is important to better understand how consumers rely on mental computation strategies as well as the consequences of doing so. To accomplish this, we discuss the relevant literature and then present the results of two lab studies.

Computational Estimation Strategies

When shopping in grocery stores, the chaotic, information-rich environment can tax a shoppers' ability to calculate the total basket price (e.g., Gourville 1998; Miller 1956). Executing many arithmetic operations with multidigit prices is demanding (Hitch 1978) and can produce physiological stress (Linden 1991), which likely results in estimation inaccuracies (Dehaene and Marques 2002). According to mathematical cognition researchers, shoppers may attempt to avoid this stress by using shortcuts or heuristics that enable them to estimate approximate total basket prices. These computational estimation strategies (Dehaene et al. 1999) include (1) rounding prices down, (2) rounding prices up, (3) rounding prices to close denominations, (4) combining compatible prices, and (5) multiplying a central price (Dehaene et al. 1999; Dowker 1992; Rubenstein 1985).[3]

1. *Round prices down*: Shoppers may round prices down to a whole dollar amount and estimate the total basket price by adding the rounded prices (e.g., $1.19 + $2.63 = $1.00 + $2.00 = $3.00) (Lemaire, Lecacheur, and Farioli 2000). Depending on the perceived cognitive costs (Stiving and Winer 1997), shoppers may adjust the final estimate to account for the rounded cents.
2. *Round prices up*: Shoppers may also round prices up to a whole dollar amount and estimate the total basket price by adding the rounded prices (Lemaire and Lecacheur 2002). In this strategy, $1.19 + $2.63 equals $2.00 + $3.00, for a total of $5.00. Depending on the cognitive costs, people may assess the rounded cents, group them, and then adjust the total estimate accordingly.
3. *Round prices to close denominations*: Shoppers also may round prices both up and down to close denominations, such as $.25, $.10, $.05, and, even, $.00 (Reys 1986). Thus, shoppers who round prices up *and* down to whole numbers ($.00) are also described by this strategy, while those who tend to round prices up *or* down to whole numbers are described with one of the previous two strategies. Using our ongoing example, shoppers rounding prices to a close denomination might estimate the sum of $1.19 + $2.63 as $3.80, using $1.20 + $2.60.
4. *Combine compatible prices*: Compatible prices add up to a number that is easier to calculate with (e.g., $1.19 + $.81 = $2.00). Shoppers who track their in-store spending may try to identify compatible prices, combine them, and then estimate the total basket price with these combined prices (Dowker 1992). For example, if a basket consists of items with four prices—$1.19, $2.63, $.82, and $1.43—a shopper might identify the following compatible numbers: $1.19 + $.82 is almost $2.00, and $2.63 + $1.43 is almost $4.00, for a basket estimate of $6.00.
5. *Multiplying the central price*: Finally, in a nonadditive strategy, consumers might estimate the total basket price by multiplying the number of items in the basket by a "central price," around which the other prices cluster (Reys et al. 1982). Consider a basket containing four items priced at $1.19, $2.63, $.82, and $1.43 (total basket price = $6.07). To estimate the total price, the shopper multiplies the central price of approximately $1.50 by the number of items (×4) to achieve an estimate of $6.00. In Table 1, we summarize these mental computation strategies.

[3]For ease of reading, we use strategy labels that differ from those proposed in mathematical cognition literature. Rounding prices down is the same as the front-end strategy, rounding prices up is better known as the rounding strategy, rounding prices to close denominations is the special numbers strategy, combining compatible prices is the compatible numbers strategy, and multiplying the central price is often known as the clustering strategy.

TABLE 1
Mental Computation Strategies to Determine the Total Price of Shopping Baskets

Mental Computation Strategies	Description	Example
Calculate exact total price	Accurately add the actual price of each individual item to assess the exact total price of the basket.	\$1.19 + \$2.63 + \$.82 + \$1.43 = \$6.07
Round prices down	Round the price of each individual item down to a whole dollar amount and add those rounded prices. Toward the end, some money may be added to compensate for the rounded cents.	\$1.19 + \$2.63 + \$.82 + \$1.43 = \$1.00 + \$2.00 + \$.00 + \$1.00 = \$4.00 (+\$2.07)
Round prices up	Round the price of each individual item up to a whole dollar amount and add those rounded prices. Toward the end, some money may be subtracted to compensate for the rounded cents.	\$1.19 + \$2.63 + \$.82 + \$1.43 = \$2.00 + \$3.00 + \$1.00 + \$2.00 = \$8.00 (–\$1.93)
Round prices to close denominations	Round the price of each individual item up or down to close denominations and add those rounded prices.	\$1.19 + \$2.63 + \$.82 + \$1.43 = \$1.20 + \$2.60 + \$.80 + \$1.40 = \$6.00
Combine compatible prices	Identify sets of compatible prices, combine them, and add the sum of these sets of prices.	\$1.19 + \$2.63 + \$.82 + \$1.43 = (\$1.19 + \$.82) + (\$2.63 + \$1.43) = \$2.01 + \$4.06 = \$6.07
Multiply the central price	Multiply the central price, or the price around which all prices cluster, by the number of items.	\$1.19 + \$2.63 + \$.82 + \$1.43 = \$1.50 × 4 = \$6.00

The Adaptive Estimator

We approach shoppers as adaptive estimators who alter their estimation strategies to the conditions on the basis of a cost–benefit analysis (Payne, Bettman, and Johnson 1988, 1993; Shugan 1980). To do so, they likely consider the perceived complexity (costs) and accuracy (benefit) of using a specific strategy in particular conditions (Johnson and Payne 1985; Senter and Wedell 1999).

In a prestudy, we determined that calculating the exact total basket price is not only perceived to offer the greatest accuracy but also considered the most complex strategy; the opposite perception emerges from multiplying the central price by the number of basket items.[4] Therefore, if shoppers select strategies solely on the basis of perceived accuracy (complexity), they should prefer calculating the exact total basket price (multiplying the central price), regardless of the estimation conditions. We propose, however, that shoppers consider both costs and benefits, weigh the importance of accuracy against the cognitive effort required, and select the most congruent strategy—that is, the strategy they perceive as offering the best combination of accuracy and complexity, given the specific estimation conditions.

Although estimators may use multiple strategies in a particular estimation condition—for example, a shopper might accurately add a few prices but round up others—Study 1 and different pilot studies imply that many shoppers rely on one dominant strategy in a given situation. To examine strategy variations across situations, we manipulate three context and task variables: price endings, shoppers' motivation to be accurate, and shoppers' estimation experience. Next, we determine which estimation strategies emerge in which conditions and measure the estimation accuracy (benefits) and complexity (costs) of the strategies in the specific conditions.

Impact of Price Endings

In Study 1, we identify rounding prices up as the dominant strategy for estimating the total prices of grocery shopping baskets, which may reflect the dominant price endings (i.e., \$.51–\$.99) in these shopping baskets. If shoppers weight the costs and benefits of a specific strategy in a particular price-ending condition, shoppers in different price-ending conditions could turn to different strategies, in that the perceived accuracy and complexity of the strategies likely depend on price endings. Consider a marketplace, such as the Study 1 store sites, in which price endings predominantly range from \$.51 to \$.99 (Schindler 2006; Stiving and Winer 1997). The shoppers likely perceive greater accuracy from rounding prices up than from rounding down (i.e., rounding up \$1.95 to \$2.00 = \$.05 difference, whereas rounding down \$1.95 to \$1 = \$.95 difference). The opposite perception might occur if price endings were to range from \$.01 to \$.49 (rounding up \$1.05 to \$2.00 = \$.95, whereas rounding down \$1.05 to \$1 = \$.05 difference).

Impact of Motivation and Estimation Experience

Incentives to improve performance tend to increase deliberation or attention to a problem; however, they also may hinder performance by stimulating people to perform actions they simply cannot do (Tversky and Kahneman 1986). For example, increasing shoppers' accuracy motivations could push them to calculate the exact total basket price. Such motivated shoppers should be willing to incur more cognitive costs to achieve higher levels of accuracy, which likely

[4]The 176 student participants in the prestudy rated the accuracy and complexity of six estimation strategies (see Table 1). These participants received a (randomized) list with instructions for each strategy and then used the first strategy on the list to estimate the total price of the first basket, which contained 19 products (each product presented sequentially). After the last item, participants rated the accuracy (1 = "not at all accurate," and 9 = "very accurate") and complexity (1 = "very easy," and 9 = "very complex") of that strategy, then moved on to the next strategy for the second basket, and so forth. The same (randomized) prices appeared in all baskets.

explains why shoppers in lower-income areas tend to try to calculate the exact total basket price (as we show in Study 1): The consequences of overspending are more detrimental for these households. However, despite their motivation to be accurate, the cognitively overtaxed shoppers may suffer greater bias and less accuracy than their less motivated counterparts because of the difficulty of calculating total basket prices accurately.

Adaptive estimation behavior also depends on prior experience with the estimation task (Payne, Bettman, and Johnson 1993). Estimation experience enables shoppers to experiment with different strategies and learn about the costs and benefits involved with each. Therefore, shoppers who have experienced the complexity of calculating an exact total basket price may adapt their strategy and instead approximate total prices of subsequent baskets.

We conduct two controlled shopping simulation studies to examine how shoppers might estimate the total prices of their shopping basket. In Study 2, we focus on the effects of price endings, and in Study 3, we examine whether and how motivation and estimation experience may influence estimation behavior and performance.

Study 2: How Price Endings Influence Estimation Behavior and Performance

To investigate whether and how price endings influence estimation behavior and performance, we undertake a laboratory experiment, involving 126 undergraduate students who received credit for their participation. The average age of the participants was 21.2 years (range: 18–33 years), and 30.2% were women.

Method

After entering the lab, participants learned that they would be presented with a shopping basket (three-second exposures to each product), for which they would estimate the total basket price and then describe, in their own words, how they arrived at that estimate (Siegler 1987).

We created four price-ending conditions for the experiment (see Appendix B). In one condition, the price endings range from \$.51 to \$.99, which approximates traditional grocery marketplaces. The second condition includes price endings ranging from \$.01 to \$.49. The third condition covers the full range of price endings, from \$.01 to \$.99. Finally, to test whether shoppers note compatible numbers, we created a condition with sets of compatible prices, such as \$.02 and \$.98. The total price of the baskets remains constant across the (between-subject) price-ending conditions.

After being randomly assigned to one of the price-ending conditions, each participant reviewed a shopping basket with 19 different products, represented in photographs from a local supermarket.[5] They viewed each photo (along with the price) sequentially for three seconds.[6] After seeing the last product, the participants wrote down their estimates of the total basket price and indicated their confidence in their estimate (1 = "not very confident," and 9 = "very confident"). Next, we asked about their perceived task complexity ("This was a complicated task," "I had difficulty keeping track," and "This was a complex calculation") on nine-point Likert scales (1 = "totally disagree," and 9 = "totally agree"; Cronbach's $\alpha = .93$).

The respondents described how they estimated the total basket price. Two independent coders, who were unaware of the research objectives and study conditions, coded each open-ended response into one of seven strategies: (1) calculate the exact total price, (2) round prices down, (3) round prices up, (4) round prices to close denominations, (5) combine compatible prices, (6) multiply the central price, or (7) other strategies. They achieved 96.0% agreement (Cohen's $\kappa = .86$, $p < .01$). Finally, participants rated their product familiarity (1 = "unfamiliar," and 9 = "familiar"; M = 6.27) and provided the name of the supermarket where they did most of their grocery shopping. None of these variables differed across study conditions ($p > .10$), nor did the sex or age of the respondents.

We operationalize the estimation bias (\$) as the difference between the estimated and the actual total basket prices. A positive (negative) estimation bias indicates that shoppers overestimate (underestimate) the basket price. Estimation accuracy (%) equals the absolute estimation bias divided by the objective total basket price (Dickson and Sawyer 1990).

Results

Few participants (9.5%) tried to calculate the exact total price of the basket, yet they were unable to do so effectively and suffered the most bias (–\$8.98 versus –\$2.78; $F(1, 124) = 5.38$, $p < .05$) and worst accuracy (18.85% versus 8.74%; $F(1, 124) = 7.72$, $p < .01$) compared with those who relied on any other estimation strategy. In addition, they rated themselves as less confident (3.62 versus 5.64; $F(1, 124) = 12.98$, $p < .05$) and as experiencing more task complexity (6.28 versus 4.31; $F(1, 124) = 12.88$, $p < .05$).

Most participants relied on computational estimation strategies, and in line with expectations, they adapted their strategy to the dominant range of price endings of items in the shopping basket ($\chi^2 = 194.45$, $p < .01$) (see Table 2). Shoppers round prices down in the \$.01–\$.49 condition, round them up in the \$.51–\$.99 condition, and round them to close denominations in the \$.01–\$.99 condition. In the condition with compatible prices, they note and combine them. These are considered the congruent strategies, the strategies that most shoppers perceive to offer the best combination of accuracy and complexity, given the specific estimation conditions.

Relying on an apparently congruent strategy seems appropriate in terms of costs and benefits. That is, congru-

[5]We identified these items in a prestudy with 30 participants from the same subject pool. These participants indicated grocery products that they bought regularly; a second prestudy revealed that the participants were familiar with the products listed (M = 6.77 [1 = "not familiar at all," and 9 = "very familiar"]).

[6]Pretests suggest that time intervals of less than three seconds make it impossible to track the total price. Intervals of more than three seconds reduce participant involvement, resulting in unrealistic estimates and strategy descriptions.

TABLE 2
Study 2: How Price Endings Influence Mental Computation Strategies

	Low Price Endings $.01–$.49 (N = 32)	High Price Endings $.51–$.99 (N = 33)	Full Range of Price Endings $.01–$.99 (N = 32)	Compatible Price Endings $.02 and $.98 (N = 29)
Calculate exact total price	9.4%	9.1%	9.4%	10.3%
Round prices down	**65.6%**	6.1%	3.1%	3.4%
Round prices up	6.3%	**69.7%**	3.1%	3.4%
Round prices to close denominations	9.4%	12.1%	**71.9%**	10.3%
Combine compatible prices	6.3%	3.0%	.0%	**72.4%**
Multiply the central price	3.1%	.0%	6.3%	.0%
Other	.0%	.0%	6.3%	.0%
Total	100.0%	100.0%	100.0%	100.0%

Notes: The percentages shown in bold highlight the congruent strategies—the strategies that most participants perceive as offering the best combination of accuracy and complexity, given the specific estimation conditions.

ent strategies yield the highest benefits, in the form of a reduced estimation bias (–$2.44 versus –$6.07; $F(1, 118) = 3.97$, $p < .05$), increased estimation accuracy (7.77% versus 15.24%; $F(1, 118) = 10.71$, $p < .01$), and higher confidence levels (5.72 versus 4.65; $F(1, 118) = 8.04$, $p < .01$). Furthermore, they lower costs in terms of the perceived task complexity (4.14 versus 4.80; $F(1, 118) = 3.29$, $p < .10$) (see Table 3).

The significant interactions in Table 3 indicate that shoppers' ability to assess the most congruent estimation strategy depends on the price-ending condition. The respondents are successful in all but one condition—namely, the $.51–$.99 condition, in which shoppers round price up, to their detriment. These shoppers are more biased (–$7.05 versus –$.54; $F(1, 31) = 3.08$, $p < .10$) and less accurate (16.15% versus 5.83%; $F(1, 31) = 3.25$, $p < .10$) than those who rely on other strategies. They also feel less confident (4.80 versus 6.38; $F(1, 31) = 6.73$, $p < .05$). However, we find no significant effect for estimation complexity (5.43 versus 4.63; $F(1, 31) = .82$, $p > .10$).

Discussion

Some people try to calculate the exact total price of their shopping basket, but most participants instead rely on computational estimation strategies, which depend on the price endings of the products in their basket. In deciding which strategy to use, the respondents seem to consider both accuracy and complexity. Whereas a focus on just one element would have increased the number of shoppers who either calculated the exact total price or multiplied the central price (as suggested by the prestudy), we find that people tend to be fairly conclusive in their assessments of the most congruent strategy for different price-ending conditions.

In general, the use of a congruent strategy makes shoppers more effective estimators than those who rely on an incongruent strategy, with one notable exception. Shoppers who round prices up when price endings predominantly range from $.51 to $.99 achieve more biased estimates than those who rely on other strategies. Study 1 confirms that people shopping in stores with these price endings predominantly round up prices; therefore, we elaborate on the potential ramifications of this tendency for consumer welfare and retail performance in the "General Discussion" section.

Study 3: How Motivation and Estimation Experience Influence Estimation Behavior and Performance

To examine the effects of motivation and estimation experience on estimation behavior and performance, we conduct a second lab study with 209 undergraduate students, who received credit for their participation. Their average age was 21.0 years (range: 18–29 years), and 36.1% were women.

Design

To examine the effects of accuracy motivations, we created a between-subjects variable, such that half the participants received an envelope with $5 as they entered the lab (high motivation condition), along with instructions that indicated that they would be estimating the total price of two baskets and that, depending on their accuracy, they could earn up to $5. The $5 would be allocated in two equal parts to each basket ($2.50 per basket), with $.25 subtracted for every $.25 increment by which their estimate differed from the actual basket price. Participants in the low-motivation condition received no cash incentive. For the within-subjects estimation experience variable, we asked all participants to estimate the total price of a second basket.

The price-ending conditions are the same as in Study 2. Both baskets again contained 19 items, and the same prices applied in both baskets (randomized). However, during the debriefing, none of the participants suspected that the prices of both baskets were the same.

Procedure

The basic procedure of Study 3 follows that of Study 2. After entering the lab, participants learned that they would be presented with two shopping baskets with multiple prod-

TABLE 3
Study 2: How Price Endings and Estimation Strategies Influence Estimation Performance

	Congruent Strategy[a]				Incongruent Strategy						
	Low Price Endings $.01–$.49 (N = 23)	High Price Endings $.51–$.99 (N = 25)	Full Range of Price Endings $.01–$.99 (N = 23)	Compatible Price Endings $.02 and $.98 (N = 21)	Low Price Endings $.01–$.49 (N = 8)	High Price Endings $.51–$.99 (N = 9)	Full Range of Price Endings $.01–$.99 (N = 9)	Compatible Price Endings $.02 and $.98 (N = 8)	Price Ending[b] F(3, 118)	Strategy Congruency[b] F(1, 118)	Price Ending × Strategy Congruency[b] F(3, 118)
Objective total price	$61.50	$61.50	$61.50	$61.50	$61.50	$61.50	$61.50	$61.50			
Estimated total price	$61.29 (3.14)	$54.45 (12.91)	$61.06 (4.65)	$59.93 (4.40)	$51.56 (11.65)	$60.96 (4.64)	$52.76 (11.35)	$57.29 (16.39)	.29	3.97**	4.31***
Estimation bias[c]	–$.21 (3.14)	–$7.05 (12.91)	–$.44 (4.65)	–$1.57 (4.40)	–$9.94 (11.65)	$.54 (4.64)	–$8.74 (11.35)	–$4.21 (16.39)	.29	3.97**	4.31***
Estimation accuracy[d]	3.75% (3.38)	16.15% (17.50)	4.98% (5.64)	5.24% (5.42)	20.51% (13.42)	5.83% (4.36)	15.48% (17.28)	18.43% (19.38)	.14	10.71***	6.92***
Estimation confidence[e]	6.65 (1.27)	4.80 (1.98)	5.78 (1.68)	5.71 (1.90)	4.22 (2.59)	6.38 (.52)	3.78 (2.17)	4.38 (2.50)	1.00	8.04***	5.94***
Estimation complexity[f]	3.41 (1.37)	5.43 (2.19)	3.77 (1.59)	3.86 (1.53)	5.37 (3.04)	4.63 (2.12)	4.70 (1.46)	4.46 (1.83)	1.10	3.29*	2.38*

*$p < .10$.
**$p < .05$.
***$p < .01$.
[a]The strategy that most estimators perceive to offer the best combination of estimation accuracy and cognitive costs, given the estimation conditions.
[b]These three columns present the F-values of the effects of price endings, strategy congruency, and their interaction on the dependent variables described in the first column.
[c]$(\text{Estimated}_{\text{basket price}} - \text{Actual}_{\text{basket price}})$.
[d]$|\text{Estimated}_{\text{basket price}} - \text{Actual}_{\text{basket price}}|/\text{Actual}_{\text{basket price}}$.
[e]Average of multi-item scale: “This was a complicated task,” “I had difficulty with keeping track,” and “This was a complex calculation” (1 = “totally disagree,” and 9 = “totally agree”).
[f]Single-item scale: “How confident are you in your estimate? (1 = “not very confident,” and 9 = “very confident”).
Notes: Standard deviations are in parentheses.

ucts and asked to estimate the total price of each. They received no intermediate feedback about their performance (Paese and Sniezek 1991). The items we used to measure perceived estimation complexity achieved high reliability (Cronbach's α = .87), and the two independent coders reached 97.0% agreement in coding the responses (Cohen's κ = .87, $p < .01$). At the end of the study, participants rated their accuracy motivation (1 = "not very motivated," and 9 = "very motivated'); those who received $5 were more motivated than those who did not (7.21 versus 6.21; $F(1, 194) = 19.56$, $p < .01$).

Results

Shopping Basket 1: effect of motivation. The results we provide in Table 4 show that more motivated shoppers are more inclined to calculate the exact total basket price than less motivated shoppers (48.9% versus 9.8%; $\chi^2 = 37.71$, $p < .01$). That is, more motivated shoppers are willing to incur more cognitive costs to be more accurate. Despite their willingness to be accurate, the estimation performance of more motivated shoppers ends up being poorer than that of less motivated shoppers. When we control for price endings and strategy congruency, multivariate analyses of variance reveal that motivation to be accurate increases estimation bias (–$2.17 versus –$6.33; $F(1, 187) = 6.74$, $p < .01$), reduces estimation accuracy (6.77% versus 13.32%; $F(1, 187) = 5.51$, $p < .05$), reduces estimation confidence (5.59 versus 4.43; $F(1, 187) = 10.34$, $p < .01$), and increases perceived task complexity (4.39 versus 4.89; $F(1, 187) = 4.02$, $p < .05$) (see Table 5).

Shopping Basket 2: effect of estimation experience and motivation. A multinomial logistic regression analysis, with the estimation strategy as the dependent variable and estimation experience, motivation, and their interaction as the independent variables, reveals that the effect of experience on estimation behavior depends on the motivation to be accurate ($\chi^2 = 10.47$, $p < .05$). As Table 4 shows, less motivated shoppers with experience barely change their estimation behavior, but more motivated shoppers with experience reduce their reliance on the calculation strategy. Whereas 48.9% of more motivated shoppers try to calculate the exact total price of Basket 1, only 3.2% use this strategy to estimate the total price of Basket 2. This change is less profound among less motivated shoppers (from 9.8% to 4.9%).

The difference in estimation performance between inexperienced and experienced shoppers also depends on their accuracy motivation (see Table 5). We control for price endings and strategy congruency and conduct a repeated analysis of variance, which shows that the difference in estimation bias between inexperienced and experience shoppers is greater for more versus less motivated shoppers (–$6.33 – –$.44 versus –$2.17 – –$1.93; $F(1, 191) = 10.46$, $p < .01$). The same is true for estimation accuracy (13.32% – 3.75% versus 6.77% – 6.02%; $F(1, 191) = 15.48$, $p < .01$) and estimation confidence (4.43 – 5.40 versus 5.59 – 6.05; $F(1, 191) = 2.90$, $p < .10$). Experienced and more motivated shoppers are less biased (–$.44 versus –$1.93; $F(1, 191) = 4.33$, $p < .05$) and more accurate (3.75% versus 6.02%; $F(1, 191) = 5.66$, $p < .05$) than experienced and less motivated shoppers. Despite their better estimation performance, experienced and more motivated shoppers feel less confident (5.40 versus 6.05; $F(1, 191) = 5.66$, $p < .05$) than their experienced, less motivated counterparts.

Additional analyses suggest that the improvement in estimation performance among more motivated shoppers results from shoppers who change their strategy. For example, the estimation bias declines from –$3.29 to –$.55 ($p > .10$) among more motivated shoppers who use the same strategy to estimate the total prices of both baskets, whereas it falls from –$9.03 to –$.39 ($F(1, 44) = 3.72$, $p < .05$) among those who change their strategy from the first to the second basket. This finding suggests that estimation experience primarily helps consumers identify better strategies rather than fine-tune their usage of a particular strategy.

Discussion

The results of Study 3 indicate that simply trying to motivate a shopper to be more accurate is likely counterproductive and may lead to even more bias and less accuracy. More motivated shoppers seem to place more weight on the perceived accuracy of mental computation strategies and opt for what they perceive as the most accurate strategy, namely, calculating the exact total price of their shopping baskets. Unfortunately, they are unable to use that strategy effectively.

Whereas motivation seems to have a counterproductive effect on estimation performance among inexperienced shoppers, it improves performance among experienced shoppers. They remain less confident than their experienced, less motivated counterparts, yet their estimation performance is significantly better. Most of the improvement seems to derive from the shift in strategies, from calculating the exact total basket price to estimating an approximate price using one of the computational estimation strategies.

On average, shoppers underestimate total basket prices, regardless of the estimation conditions and their accuracy motivations. If this underestimation tendency influences their spending behavior, it has critical implications for consumer welfare and retail performance.

Study 4: Effect of Estimation Biases on In-Store Spending Behavior

To investigate whether estimation biases are related to in-store spending behavior, we intercepted 128 shoppers in checkout lines in a midwestern supermarket. The store was located in a zip code area with an average annual household income of $52,628 (poverty rate = 9.7%). The average age of the participants was 40.3 years (range: 18–78 years), and 85.2% were women.

Method

One of three trained interviewers approached shoppers who were waiting in checkout lines at different times during the week and asked them to participate in a five-minute, university-supported study on shopping behavior. Before completing the checkout process and paying for their gro-

TABLE 4
Study 3: How Price Endings, Estimation Experience, and Motivation Influence Mental Computation Strategies

	Basket 1 (t = 1)				Basket 2 (t = 2)			
Low Motivation (N = 102)	**Low Price Endings $.01–$.49 (N = 27)**	**High Price Endings $.51–$.99 (N = 25)**	**Full Range of Price Endings $.01–$.99 (N = 27)**	**Compatible Price Endings $.02 and $.98 (N = 23)**	**Low Price Endings $.01–$.49 (N = 27)**	**High Price Endings $.51–$.99 (N = 25)**	**Full Range of Price Endings $.01–$.99 (N = 27)**	**Compatible Price Endings $.02 and $.98 (N = 23)**
Calculate exact total price	11.1%	8.0%	11.1%	8.7%	3.7%	4.0%	7.4%	4.3%
Round prices down	**74.1%**	4.0%	3.7%	8.7%	**81.5%**	4.0%	3.7%	.0%
Round prices up	3.7%	**72.0%**	3.7%	4.3%	3.7%	**84.0%**	.0%	.0%
Round prices to close denominations	7.4%	12.0%	**74.1%**	4.3%	7.4%	4.0%	**88.9**%	.0%
Combine compatible prices	3.7%	4.0%	.0%	**73.9%**	3.7%	4.0%	.0%	**91.3%**
Multiplying the central price	.0%	.0%	3.7%	.0%	.0%	.0%	.0%	.0%
Other	.0%	.0%	3.7%	.0%	.0%	.0%	.0%	4.3%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
High Motivation (N = 94)	**(N = 24)**	**(N = 23)**	**(N = 23)**	**(N = 24)**	**(N = 24)**	**(N = 23)**	**(N = 23)**	**(N = 24)**
Calculate exact total price	50.0%	52.2%	47.8%	45.8%	4.2%	.0%	4.3%	4.2%
Round prices down	**41.7%**	4.3%	.0%	.0%	**87.5%**	4.3%	.0%	.0%
Round prices up	.0%	**39.1%**	.0%	.0%	4.2%	**82.6%**	4.3%	4.2%
Round prices to close denominations	8.3%	4.3%	**43.5%**	8.3%	4.2%	8.7%	**82.6%**	8.3%
Combine compatible prices	.0%	.0%	4.3%	**45.8%**	.0%	4.3%	4.3%	**83.3%**
Multiplying the central price	.0%	.0%	4.3%	.0%	.0%	.0%	4.3%	.0%
Other	.0%	.0%	.0%	.0%	.0%	.0%	.0%	.0%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Notes: The percentages shown in bold highlight the congruent strategies—the strategies that most participants perceive as offering the best combination of accuracy and complexity, given the specific estimation conditions.

TABLE 5
Study 3: Estimation Experience and Motivation Influence Estimation Performance[a]

	Basket 1 (t = 1)		Basket 2 (t = 2)				
	Low Motivation (N = 102)	High Motivation (N = 94)	Low Motivation (N = 102)	High Motivation (N = 94)	Estimation Experience[b] F(1, 191)	Motivation[b] F(1, 191)	Estimation Experience × Motivation[b] F(1, 191)
Objective total price	\$61.50	\$61.50	\$61.50	\$61.50			
Estimated total price	\$59.33 (6.68)	\$55.17 (10.01)	\$59.57 (6.04)	\$61.06 (3.54)	9.26***	.59	10.46***
Estimation bias[c]	–\$2.17 (6.68)	–\$6.33 (10.01)	–\$1.93 (6.04)	–\$.44 (3.54)	9.26***	.59	10.46***
Estimation accuracy[d]	6.77% (9.17)	13.32% (13.88)	6.02% (8.36)	3.75% (4.41)	14.35***	1.14	15.48***
Estimation confidence[e]	5.59 (1.88)	4.43 (2.05)	6.05 (1.84)	5.40 (1.83)	4.59**	10.12***	2.90*
Estimation complexity[f]	4.39 (1.65)	4.89 (1.65)	4.01 (1.69)	4.35 (1.75)	5.73**	3.97**	.74

*$p < .10$.
**$p < .05$.
***$p < .01$.
[a]We control for the main and moderating effects of price conditions and strategy congruence.
[b]These three columns present the F-values of the effects of estimation experience, motivation, and their interaction on the dependent variables described in the first column.
[c]$(\text{Estimated}_{\text{basket price}} - \text{Actual}_{\text{basket price}})$.
[d]$|\text{Estimated}_{\text{basket price}} - \text{Actual}_{\text{basket price}}|/\text{Actual}_{\text{basket price}}$.
[e]Average of multi-item scale: “This was a complicated task,” “I had difficulty with keeping track,” and “This was a complex calculation” (1 = “totally disagree,” and 9 = “totally agree”).
[f]Single-item scale: “How confident are you in your estimate?” (1 = “not very confident,” and 9 = “very confident”).
Notes: Standard deviations are in parentheses.

ceries, respondents estimated the total price of their shopping basket and then answered a series of shopping-related questions pertaining to the number of times per month they shopped for groceries, whether they kept track of their spending while shopping, whether they had a maximum dollar limit that they planned to spend during this trip (i.e., whether they were shopping on a budget), and, if so, how much they planned to spend ($). In addition, the interviewers noted respondents' age and sex. After the respondents paid for their groceries, the interviewer investigated a copy of their receipt to determine the total basket price, handed the receipt to the shoppers, and thanked them for their participation.

Results and Discussion

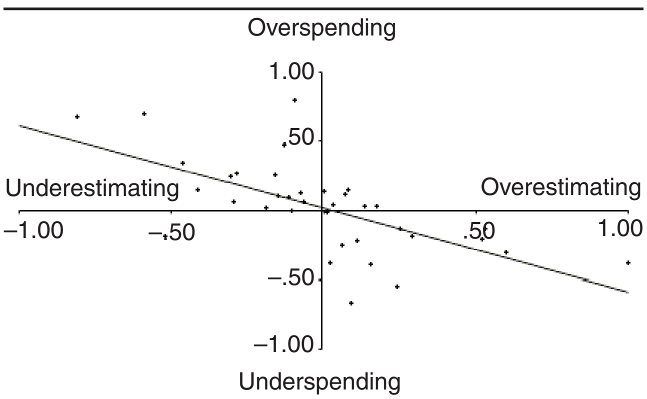
Budget shoppers are twice as likely to track their in-store spending than those who shop without a budget (77.8% versus 36.7%; $\chi^2 = 12.59$, $p < .01$). To determine whether shoppers' estimation biases were related to their in-store spending, we consider only budget shoppers who track their in-store spending (N = 46) because we need some spending norm to calculate any spending bias. To correct for differences in total basket prices (e.g., larger versus smaller trips), variations in estimation biases associated with these different shopping trips (e.g., smaller biases for smaller trips), and general response biases that may influence self-reported budgets and basket estimates, we standardize each individual measure.

Consistent with our expectations, we find a significant, positive correlation between estimation biases (estimated amount – actual amount) and spending biases (budget amount – actual amount) (r = .56, $p < .01$). As Figure 1 shows, the more shoppers underestimate their total basket price, the more they overspend relative to their budget; more cautiously, they appear to be at an increased risk of spending more than their budget. Thus, estimation biases may have implications for not just retail performance but also consumer welfare.

General Discussion

In two laboratory studies and two field studies, we examine how budget-minded grocery shoppers track their in-store spending. The results suggest rich implications for consumer welfare and retail pricing and for understanding how shoppers use computational estimation strategies.

FIGURE 1
Study 4: Price Estimates of Baskets Influence Spending Biases



People adapt their strategies to the dominant range of price endings in their baskets. By relying on the strategy they believe to be most congruent with a specific price-ending condition, they attain the most accurate estimates in all but one condition. Therefore, price endings influence not only price perceptions (e.g., Schindler 2006), sales demand (Anderson and Simester 2003), and price discount perceptions (Coulter and Coulter 2007) but also, at the aggregate level, estimation behavior and performance.

The results further indicate that working memory constraints may hinder shoppers' ability to calculate the exact total price of their shopping baskets, resulting in more biased, less accurate, and less confident estimates than those attained by shoppers who rely on computational estimation strategies to estimate an approximate total price. This unintended consequence may help explain the evident paradox between wanting to be more accurate and actually being more accurate. Motivated estimators try harder, but they do worse. Despite their greater inclination to calculate the exact total basket price, they cannot effectively employ this strategy. The opposite is true for motivated shoppers with experience; they are more accurate because they more effectively rely on computational estimation strategies than experienced, less motivated shoppers.

Implications for Consumer Welfare

The process of budgeting is challenging because it forces people to make difficult trade-offs between spending money on necessities and nonessential luxuries (Kivetz and Simonson 2002). Actually spending in accordance with such self-imposed budgets is even more cumbersome (Cheema and Soman 2006). To stay within budget, shoppers must know how much they are spending, and these estimates directly determine how much they spend.

When consumers are inaccurate, they suffer consequences. First, shoppers who overestimate the total basket price likely spend less than they budgeted for—that is, they do not maximize their own utility under the budget constraint (Hymans and Shapiro 1976). Furthermore, they might reallocate the "saved" money to a different (mental) account (Soman and Cheema 2001), which could entail a financial loss for the retailer. Second, shoppers who underestimate the total basket price are more likely to spend more than their grocery budget, in which process they unintentionally reallocate more money to the "grocery account" (Soman and Cheema 2001). In turn, this reallocation may trigger a chain of budget and spending decisions that could cause shoppers significant financial distress.

Across the studies we report, shoppers consistently underestimate the total price of shopping baskets, which puts them at risk for spending more than they budgeted. Those who try to calculate the exact total price of their basket appear to be at the greatest risk of underestimating the total price, by up to $8.98 (18.9%). Because motivated shoppers appear to be most inclined to calculate the exact total basket price, the results indicate that shoppers with tight budgets, who are most motivated to be accurate, may also be most at risk for spending more than their budget.

Estimation experience helps shoppers become more effective and confident estimators, but not all experienced estimators rely on the most congruent strategies. Therefore, there may be some value in training shoppers. In general, training people about the principles of decision making, statistics, and mental computation enhances performance (Reys 1986); it also may improve basket estimations. Educating shoppers about computational estimation strategies may enable them to become more informed shoppers, turning wild guesses into more educated ones. In turn, consumer welfare should improve because shoppers can maximize their utility given their budget while minimizing the likelihood of spending more than they can afford.

Managerial Implications

Consequences. For many retailers, price-setting strategies are one of their top priorities (Bell and Lattin 1998). In general, retail price-setting strategies are molded by research that focuses on the consequences of price endings for individual items rather than for a shopping basket that contains multiple items. This research provides unique insights that suggest instead that setting prices one item at the time could have negative consequences for retailers.

In general, research on the effect of price endings assumes that shoppers ignore, or pay less attention to, the rightmost two digits when evaluating the prices of individual products (Monroe 2003). Therefore, pricing products at $.01 below a whole number (e.g., $4.99 instead of $5) increases purchases of individual items (Anderson and Simester 2003). Retail managers often receive advice to use high numbers, such as 9, in price-ending digits to maximize their profitability (Gedenk and Sattler 1999; Stiving and Winer 1997). Although this price-setting strategy may maximize profitability with respect to individual items, it does not necessarily do so for the overall shopping trip. Shoppers may ignore the rightmost digits when evaluating the prices of individual items, but our research suggests they do not when they estimate the total basket price. Instead, the price-setting strategy stimulates shoppers to round prices up to whole dollar amounts, putting them at risk to overspend, which may negatively influence their perceptions of the retailer and, thus, retail performance.

Possible solutions. Setting retail prices in accordance with research into the prices of individual items alone may have negative consequences for retailers. In addition to changing their price-setting strategies, retailers should consider helping customers become more accurate estimators by informing them about and training them on computational estimation strategies. Retailers also could invest in the growing array of technical solutions that enable shoppers to track in-store spending accurately. For example, shopping cart scanners enable shoppers to track the total basket price exactly while they shop (e.g., www.cuesol.com).

Alternatively, retailers might benefit from the growing number of products that are marketed with radio frequency identification (RFID) tags. A 2004 survey of U.K. consumers indicated that 72% would accept RFID tags on products in exchange for better tracking of their in-store spending totals (www.infosys.com). By enabling customers to become more confident and accurate estimators, retailers help improve consumer welfare and mitigate the potential negative consequences of common price-setting strategies, especially during economic downturns. These recommendations pertain mainly to shoppers who intend to track their in-store spending; research on the implications of these solutions for shoppers who normally do not track how much they are spending is also necessary.

Limitations and Directions for Further Research

Because this research addresses an important topic in a new research area that has received little prior attention, our empirical findings, though clear and unequivocal on their own, represent a starting point for further research into the in-store tracking behavior of shoppers in general and their reliance on mental computation strategies specifically. For example, our lab findings should be tested in an actual grocery context to confirm the external validity of the effects of price endings and motivation. Extending this research to other contexts and additional consumer groups might help generalize our understanding of how people determine the total prices of their shopping baskets. For example, research might examine whether shoppers use the same strategies during different types of shopping trips (e.g., groceries versus durables, planned versus unplanned trips) and whether they use computational estimation strategies during shopping trips for fewer items. Although computational estimation strategies may seem less relevant when shopping for only a few items, research suggests that the complexities of adding just two prices can induce people to rely on them (Dehaene and Marques 2002; Hitch 1978).

This research strongly suggests that people rely on a dominant strategy, but added research could examine whether, to what extent, and in which conditions people actually use multiple strategies. In this sense, it would be critical to learn more about the individual computational estimation strategies. When rounding prices up or down to a whole dollar amount, when and how do people determine by how much to correct the final estimate to account for the rounded cents? When rounding prices to close denominations, what determines the specific denomination? When combining compatible prices, how compatible must the prices be (e.g., $1.20 and $.80 versus $1.22 and $1.83)? When multiplying the central price by the number of basket items, how do people determine the central price, and how accurate are they? A better understanding of these individual estimation strategies will yield insights into the discrepancies between the objective accuracy of a strategy—obtained by strictly applying the estimation strategies—and the subjective accuracy—obtained by the shoppers who apply the strategy.

The relationship among price endings, perceived estimation accuracy, and the complexity of the individual estimation strategies also demands closer examination to determine what makes people believe that a particular strategy will be most accurate and least complex, given an individual price ending or set of price endings, as well as how long it takes them to make this determination. Finally, research should investigate how shoppers weigh the costs and benefits of using a strategy in a specific estimation context.

Because of the negative ramifications of underestimated basket prices for both consumer welfare and retail performance, it seems relevant to gain a better understanding of why people tend to under- rather than overestimate total basket prices. Considering the real-world relevance, specific attention should focus on why rounding prices up when price endings range between $.51 and $.99 results in underestimation biases. Keeping track of the rounded cents (Thomas and Morwitz 2005) and the change in the leftmost digits (e.g., from $3.99 to $4.00) (Hitch 1978) would complicate the use of this strategy and may contribute to underestimation biases.

Feedback about estimation performance also may significantly influence the effect of experience. Participants who perform better (worse) than expected might be less (more) inclined to change their strategy, so further research should address the implications of performance feedback. Such feedback likely mimics real shopping behavior more closely, which may help explain why a relatively high percentage of (experienced) shoppers seem to rely on apparently suboptimal strategies to estimate their total basket price.

Finally, additional research on the impact of price endings in shopping baskets should go beyond total basket price estimates. Research could examine whether and how the dominant range of price endings in a shopping basket influences perceptions of basket value, the shopping experience, and the store's price image. Furthermore, researchers should verify the suggested relationship between estimation biases and store satisfaction, which we examined using self-reported measures, and extend it to store price image and store loyalty. By investigating multiple shopping tasks and baskets, researchers might gain a stronger understanding of the long-term effects of common price-setting strategies that retailers use.

APPENDIX A
Study 1: Price-Ending Comparisons of Highly Consumed Product Categories

Product Category	Description	Brands	SKU	Prices in Lower-Income Store	Prices in Higher-Income Store
Dairy products	Milk	Store brand	½ gallon	$2.49	$2.39
			1 gallon	$3.79	$3.59
		Mayfield	½ gallon	$2.99	$2.89
			1 gallon	$4.99	$5.59
Vegetables and potatoes	Fresh green beans		1 lb.	$1.39	$1.49
	Regular carrots		1 lb.	$.89	$.78
	Baby carrots		1 lb.	$1.79	$1.99
	Potatoes	Russett	8 lbs.	$3.99	$3.79
		Idaho	4 lbs.	$2.69	$2.79
	Canned green beans	Allens	14.5 oz.	$1.43	$1.09
			28 oz.	$2.49	$2.29
		Del Monte	14.5 oz.	$1.39	$1.29
	Canned carrots	Store brand	14.5 oz.	$.99	$.75
Fruits and fruit juices	Apples	All varieties	3 lbs.	$3.99	$2.97
	Oranges	Florida	4 lbs.	$2.60	$2.98
	Apple juices	Nestlé	46 oz.	$2.89	$2.99
		Mottis	64 oz.	$3.35	$3.29
		White House	46 oz.	$2.39	$2.39
		Old Orchard	64 oz.	$2.59	$2.98
	Orange juices	Sunny Delight	64 oz.	$2.69	$2.89
		Tropicana	64 oz.	$3.59	$3.99
			1 gallon	$6.79	$6.99
		Store brand	64 oz.	$2.49	$2.49
Cereals		Kellogg's	18 oz.	$3.99	$3.89
		Cheerios	18 oz.	$5.09	$4.69[a]
			14 oz.	$3.89	$3.69
Meat	T-bone steak		1 lb.	$7.99	$6.99
	Beef		1 lb.	$3.99	$3.89
	Ground beef		1 lb.	$1.59	$2.49[a]
	Pork chops		1 lb.	$3.89	$3.69
	Chicken		1 lb.	$1.99	$1.99
Eggs			12 large, A	$1.89	$1.79
Carbonated beverages		Coca-Cola	2 liters	$1.69	$1.55
		Pepsi	2 liters	$1.49	$1.39
		Red Rock Cola	2 liters	$.99	$.89

APPENDIX A
Continued

Product Category	Description	Brands	SKU	Prices in Lower-Income Store	Prices in Higher-Income Store
Bread		Store brand	1 loaf	$1.49	$1.49
		Nature's Own	1 loaf	$2.50	$2.50
		Sunbeam	1 loaf	$2.69	$2.69
		Colonial	1 loaf	$2.69	$2.69
Chips		Lay's Classic	6¾ oz.	$2.29	$3.29
			11 oz.	$3.99	$3.99
Beer		Heineken	6 bottles	$8.69	$8.49[a]
		Budweiser	6 cans	$5.69	$5.99
			6 bottles	$5.69	$5.99
		Miller	18 cans	$10.99	$9.99
Toilet paper		Store brand	4 rolls	$1.77	$1.69
		Cottonelle	6 rolls	$6.99	$5.99
		Angel Soft	12 rolls	$8.49	$8.39
		Scott	12 rolls	$11.99	$9.99
		Charmin	26 rolls	$8.55	$8.79
Total				$187.66	$183.58
Average				$3.75	$3.67

[a]Price endings differ between both stores ($.01–$.49 versus $.51–$.99).

APPENDIX B
Price Levels in Studies 2 and 3

Number of Items	Low Price Endings: $.01–$.49	High Price Endings: $.51–$.99	Full Range of Endings: $.01–$.99	Compatible Endings: $.02 and $.98
1	$1.01	$.99	$.95	$.99
2	$1.01	$.99	$1.09	$1.01
3	$1.19	$.81	$1.19	$2.30
4	$3.19	$3.81	$3.59	$3.70
5	$1.15	$1.85	$1.50	$1.15
6	$2.19	$2.81	$2.59	$2.85
7	$2.39	$2.61	$2.61	$2.61
8	$1.35	$.65	$.72	$1.39
9	$3.13	$2.87	$2.87	$2.90
10	$4.11	$3.89	$4.11	$4.10
11	$3.29	$3.71	$3.29	$3.30
12	$5.29	$5.71	$5.71	$5.70
13	$2.18	$1.82	$2.29	$.81
14	$4.28	$3.72	$4.30	$3.19
15	$1.48	$1.52	$1.50	$1.50
16	$6.11	$5.89	$5.99	$6.50
17	$8.05	$7.95	$7.00	$7.05
18	$7.09	$6.91	$6.91	$6.95
19	$3.01	$2.99	$3.29	$3.50
Total	$61.50	$61.50	$61.50	$61.50

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