Consumer Search:
Evidence from Path-Tracking Data*

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This draft: July 8, 2014

We estimate the effect of consumer search on the price of the purchased product in a physical store environment. The analysis is implemented using a unique data-set obtained from radio frequency identification tags which are attached to supermarket shopping carts. This allows us to record consumers’ purchases as well as the time they spent in front of the shelf when contemplating which product to buy, giving us a direct measure of search effort. Controlling for a host of confounding factors we estimate that an additional minute spent searching lowers price paid by $2.20.

JEL Classification:

Keywords: Consumer Search, In-Store Marketing, Path Data

*We thank Swati Yanamadala for excellent research assistance. We are grateful to Herb Sorenson for providing us access to the data and to Herb and Jamin Roth for helping us to understand the data better. We would like to thank seminar participants at Toronto, Michigan, Boston College, Chicago, UC Davis and conference participants at EARIE (Évora), the Choice Symposium (Noordwijk), IIOC (Chicago) and Marketing Science (Atlanta) for great feedback. We also benefitted greatly from discussions with Emek Basker, Eric Bradlow, Daria Dzyabura, Pedro Gardete, Matt Gentry, Jonathan Haskel, Ella Honka, Alessandro Iaria, Guy Michaels, Chris Nosko, David Rapson, Navdeep Sahni, John Van Reenen, Matthijs Wildenbeest and Song Yao. All errors are our own.
1 Introduction

When consumers make a purchase decision they might often not be aware of prices for all products due to informational and cognitive constraints. In many categories, a large number of products is available and obtaining relevant information can be a costly process. In a grocery shopping context, consumers can search across stores, time their purchase in order to benefit from temporary price reductions, and search across various products within a particular store when standing in front of the shelf. In this paper, we focus on the final part of this decision process: the consumer’s search-effort when processing information and comparing products and prices immediately before putting the chosen product into her shopping cart. Specifically, our goal is to estimate the effect of the extent of consumers’ search activity within a particular product category on the price they pay.

A key challenge in analyzing consumer search behavior in a physical store environment lies in the fact that it is hard to observe and record which products the consumer was considering before picking one particular product from the shelf. This is different from studies using online data such as De Los Santos, Hortacsu, and Wildenbeest (2013), Koulayev (2013) or Chen and Yao (2014) where one typically observes the sequence of searches. An alternative in a brick and mortar environment would be to provide consumers with eye-tracking equipment as in Stütten, Boatwright, and Monroe (2012). This provides a great level of detail but has the disadvantage of disrupting the “natural” shopping experience of the consumer. In this paper we propose an approach to understanding search behavior without such an intervention. To this end we use “path-tracking” data obtained from shopping carts that are equipped with radio-frequency identification (RFID) tags combined with store-level data on purchases and product prices. The data allows us to measure the time a consumer spends in front of a particular category before deciding to purchase a specific product, thus giving us a direct measure of the extent of the consumer’s search activity.

The central contribution of the paper is to demonstrate how the monetary benefits from search (per unit of time) can be estimated using data on the total duration of search as well as the price of the chosen product. To the best of our knowledge this, in parallel with Jain, Misra, and Rudi (2014), is the first paper to gather data on search effort and to estimate search benefits in a physical store environment. Using a reduced-form approach, where we regress price paid on search-time in a linear regression framework, we find that an additional minute spent searching lowers expenditure by $2.20. The magnitude is economically significant: Extending search-time by one standard deviation in each product category lowers total trip-level expenditure by 8 percent on the average shopping trip. Given that we are analyzing very frequently purchased products, the potential unrealized savings are large and suggest that consumers engage in a limited amount of search activity. We also find that search activity varies greatly across different areas of the store which suggests one possible channel through

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1 A further source of data on consumer search behavior / considerations is survey information directly levied from consumers. This kind of data is used in Dragnska and Klapper (2011) and Honka (2014).

2 Apart from RFID other technology such as video capture (see Jain, Misra, and Rudi (2014) or Hui, Huang, Suher, and Inman (2013)) or smart-phone wi-fi signals might also be used to measure search-time in a similar fashion.
which product placement and store design can influence consumer behavior. Moving a product category from the area with lowest to the area with the highest level of search activity leads to an increase in search time of almost 16 seconds (2 standard deviations), which decreases price paid by $0.60 and increases the probability of purchasing a promoted product by 13 percentage points. The magnitude of this effect is large and relevant for manufacturers who pay slotting allowances to place their products in certain locations inside the store. Based on search-time differences, some locations do engender closer competition with other brands due to consumers engaging in more search. Similarly, pricing decisions should arguably be a function of product location. In high search locations running a promotion will be more effective than in areas of the store where consumers’ search effort is lower.

In order to guide our empirical analysis, we rely on the canonical sequential model of consumer search (McCall (1970)), which we use to derive predictions for the relationship between search-time and price paid in response to variation in consumers’ search costs. Our objective is to empirically uncover how an increase in search-time due to lower consumer search costs translates into a lower price paid. To this end we need to isolate variation in search-time that is due search cost differences rather than other factors. While a more in-depth discussion is relegated to a later point, we present the key concerns and identification assumptions here. Using the sequential search model, we identify two other determinants of search-time variation. First, consumers face different price distributions over time within each category due to promotional activity and, most importantly, drawing prices from a more “favorable” price distribution leads to shorter search-spells as well as a lower price paid. Second, consumers with the same search cost will in general draw different prices from a given distribution during their respective search process. In other words, pure chance when drawing prices will lead to variation in search-time. We show that this variation in search-time does not affect the price paid and will therefore lead to attenuation bias in our estimate. A final concern is due to the nature of our data: we are able to record the time a consumers spends in the vicinity of the product category, which is a noisy measure of actual category-level search activity. The presence of this measurement error will lead to attenuation bias in an OLS regression.

In order to address all of the concerns above we need to use search cost shifters as instruments for search duration. We leverage the fact that we have information on consumer purchases as well as in-store behavior for the whole trip of which search activity within each category makes up only a small part. Specifically, we use the consumers’ walking speed over the course of the trip, the total number of items purchased, and a dummy for whether the consumer used a basket (rather than a shopping cart) as instruments for search-time. The identifying assumption is that overall trip behavior such as walking speed and basket size is driven by exogenous variation in consumption needs and search-costs. For instance con-

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Note that promotional variation over time is variation that could be used under the assumption that the timing of promotional activity is exogenous. However, one would need to take a more structural approach in order to use this variation. For instance the fact that in a week with more promotions, search-time decreases by a certain amount, does tell us something about the search process. In order to make a statement about search costs, one would need to take a stance on how expectations are formed which is something our approach avoids. Similarly, a structural model could explicitly account for the role of chance in the search process.
sumers might go shopping on the weekend where they are not in a rush. This trip would be characterized by a larger basket size and slower walking speed relative to a quick fill-in trip at lunch-time on a weekday. Most importantly, we assume that the price distribution of any particular category and luck in the search process do not influence walking speed, basket size and the choice between using a basket or cart.

There are two main caveats to our analysis. First, our data covers only a short period of time and, although we do observe some consumers repeatedly in the path-tracking data, the panel dimension is too small to exploit. Our estimation can therefore be thought of as essentially cross-sectional. This is not unique to our setting and indeed all empirical papers on consumer search that we are aware of are cross-sectional in nature (Kim, Albuquerque, and Bronnenberg (2010), De Los Santos, Hortacsu, and Wildenbeest (2013), Koulayev (2013), Honka (2014)). The main drawback that the lack of a panel dimension creates in our setting is the inability to control for consumer preferences through repeated observations for the same consumer. This is a concern to the extent that search costs and therefore search-spell duration is correlated with consumers’ price sensitivity. If more price sensitive consumers also have lower search costs we are likely to overestimate the effect of search on price paid. While search-time is conceivably correlated with price sensitivity, it is less clear whether this is also the case for our instruments. Nevertheless, we run a set of additional robustness checks to address this concern. Specifically, our setting allows us to control for heterogeneity in preferences by using variation in search activity within consumers across different categories (mostly on the same trip) as well as panel data on purchases (but not search).

Second, we have to pool the search-data across categories due to the fact that we do not have enough observations at the individual category level. Having to deal with data across 150 categories and 30,000 UPCs prevents us from modeling utility across products more broadly and we instead focus on the effect of search on price. Undoubtedly, price is not the only relevant product characteristic in CPG categories, and our approach therefore only captures one aspect of the search process. However, the effect of search on price is relevant for informing product location and pricing decisions as we demonstrate in more detail later.

Our paper contributes to various streams of literature. It is closely related to a series of seminal papers by Hui, Bradlow and Fader (Hui, Fader, and Bradlow (2009), Hui, Bradlow, and Fader (2009a), and Hui, Bradlow, and Fader (2009b)) which introduced path-tracking data to the marketing literature. Relative to their work, which jointly describes the path as well as purchase decisions of consumers, we make little use of the actual path the consumer takes. Instead, we focus more narrowly on the consumer’s search process when standing in front of the shelf containing a particular product category. In addition to the path-data,
we also make use of detailed product-level price and purchase data that we are able to link to the path-tracking data-set. The combination of the two data sources allows us to analyze how consumers’ search duration (recorded by the path-data) impacts the purchases they make (measured in the sales data). In this way we are able to link the novel information we can get out of the path-tracking data to the literature on consumer search and consideration set formation. To the best of our knowledge, when analyzing consideration sets in a physical store context (see for example Roberts and Lattin (1991), Andrews and Srinivasan (1995), Bronnenberg and Vanhonacker (1996), Mehta, Rajiv, and Srinivasan (2003) and Seiler (2013)), the search process was usually unobserved. In this paper we instead have a direct measure of the extent of search activity. As mentioned before, one notable exception is Jain, Misra, and Rudi (2014) who also observe search behavior in a physical store environment via video capture.

The other strand of literature the paper contributes to is a set of papers on consumer search that uses data on the search process such as Kim, Albuquerque, and Bronnenberg (2010), De Los Santos, Hortacsu, and Wildenbeest (2013), Koulayev (2013), Honka (2014) or Chen and Yao (2014), mostly in the online realm. Relative to those papers, we take a more reduced-form approach to modeling search benefits rather than estimating a search model structurally. This has some advantages and drawbacks. Our setting allows us to deal with measurement error in search effort which is presumably present in many setting. However, usually the search effort or search sequence enters a highly non-linear model. Instead, in our linear setting, instrumental variables provide a simple solution. Second, we do not need to make assumptions about consumers’ information sets and expectation formation, which are crucial identifying assumption in most structural search models. On the other hand, without a more structural approach, we are not able to model consumer utility and choice as a function of product characteristics more broadly and instead focus solely on price. Finally, our approach does not lend itself easily to interesting counterfactuals such as search cost reductions which could be achieved through various marketing tools. To a large extent the approach is motivated by the nature of our data. Nevertheless, we believe that our approach has certain advantages over more structural ones and we see it as a novel way of using search data that is complimentary to previous approaches.

The remainder of the paper is organized as follows. Section 2 provides a detailed explanation of the data used in our analysis and descriptive statistics. In section 3, we provide a theoretical framework to guide our empirical strategy and discuss identification. In section 4 we present the main results, followed by robustness checks. In section 5 we provide some interpretation for the magnitude of the estimated effect. In section 6 we explore the effect of product location on search and purchase behavior. Finally we make some concluding remarks.

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7A small number of studies on consumer search in a physical store environment such as Cobb and Hoyer (1985) or Dickson and Sawyer (1990) and Hoyer (1984) employed teams of trained investigators, who observed consumers in the store and recorded their search-time manually. This allows them to record search-duration albeit only for a relatively small sample of consumers.

8For instance Honka (2014) uses self-reported data on which products were considered. De Los Santos, Hortacsu, and Wildenbeest (2013) assume that every visit to an online bookstore in the week prior to a purchase from the search history for that specific title.
2 Data

We use data from a large store in Northern California that belongs to a major supermarket chain. The complete dataset comprises three pieces: (1) sales data from the supermarket, (2) a store-map with information on product-locations, (3) data on the path a consumer took through the store for a subset of trips over a period of 26 non-consecutive days. Importantly, we are able to link the path-data to the corresponding purchase baskets from the sales data with the help of the store map. In Section A.1 of the appendix we provide details on how the two pieces of data are combined.

We have complete purchase data for all consumers that visited the store during the 26 days for which we also observe the path-data. This part of the data is a standard supermarket scanner data-set similar to the IRI dataset (see Bronnenberg, Kruger, and Mela (2008)) for instance. At the consumer-level, we observe the full basket of products as well as the price paid for each item. Unfortunately, prices for items that do not come in specific pack-sizes (e.g. fresh fruit, vegetables, meat etc.) are not reported in meaningful units (i.e. per kilogram for instance). We are therefore unable to use those products in our analysis. Apart from these problematic products we are going to use data from about 150 different product-categories which are stocked in the store. Over our sample period, we observe a total of about 220,000 shopping baskets. However, the path-data is only available for a subset of those.

2.1 Path data

In addition to the sales data we also have data on the path that consumers took when walking through the store. The paths are obtained using RFID tags that are attached to consumers’ shopping carts and baskets (see Sorensen (2003)). Each RFID tag emits a signal about every 4 seconds that is received by a set of antennas throughout the store. Based on the signal, triangulation from multiple antennas is used to pin-point the precise location of the consumer. The consumer’s location is then assigned to a particular point on a grid of so-called “traffic-points” which is overlayed onto the store-map. The points used to assign consumers’ locations are four feet apart from each other, allowing for a fairly granular tracking of the consumer. For every path we observe a sequence of consecutive traffic points with a time stamp associated to each point.

However, not all shopping carts and baskets in the store are equipped with RFID tags. We only observe path-data for a subset of about 7 percent of all store visits. This is somewhat limiting as we rarely observe multiple trips for the same consumer despite the fact that we have more of a panel dimension in the purchase data. We will discuss how this affects our analysis later when we present the empirical strategy. Second, even if a shopping basket is matched to the path-data, it is possible that not all purchased items in the basket have a

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9We are not able to disclose the identity of the supermarket. The store has a fairly typical format with a trading area of about 45,000 square-feet and a product range of 30,000 UPCs.


11If a consumer moves further than to an adjacent traffic point between signals, the movement over traffic points in between the signals is interpolated. As the signal is emitted at a high frequency little interpolation is necessary for most trips.
match in the path-data. This can happen if the consumer leaves her cart or basket behind and the item pick-up will not be captured in the data.

The primary variable of interest derived from the path-data is the time a consumer spends stationary at a certain point in the store when picking up a product. An individual item purchase, or more precisely the “pick-up” of the item from the shelf, constitutes the unit of observation in our regressions and we observe a total of around 34,000 pick-ups in the data. Using the store map we match the grid of traffic points to product locations that are within reach of the consumer from a given traffic point. For a given path and set of products in the basket at the check-out, we can then use the store map to determine when the product was picked up by the consumer as well as how long she spent in front of the shelf. In other words, the item pickup is defined as the moment in time the consumer walked past a specific product that we later see in her purchase basket. In order to compute search-time, we measure the time elapsed between (1) the moment the consumer is first located on a traffic point assigned to the product and (2) the point in time when she moves on to a traffic point outside of the assigned area. Figure 1 illustrates graphically how search-time is assigned to a product pick-up. This metric gives us a measure of time spent in the vicinity of the product which was ultimately purchased. For convenience of exposition, we will refer to this metric as search-time. However, we recognize that it is a noisy measure of actual search activity and the consumer might have been doing other things at the same time. The presence of such measurement error will inform our empirical strategy later. Figure 2 shows the histogram for our search metric across item pick-ups. The variable is roughly log-normally distributed with a mean of 10.3 seconds and a standard deviation of 8.5 seconds.

Furthermore, we also compute the speed at which the consumer moves over the course of the trip using time-stamps and distances between consecutive traffic points. Speed, although not the primary focus of this paper will play role in our empirical strategy. Basic descriptive statistics for the key variables used in the empirical analysis are reported in the top two panels of Table 1. These include trip characteristics such as average speed throughout the trip and trip duration as well as the pick-up specific measure of search-time and price paid.

### 2.2 Price Dispersion and Possible Savings from Search

The empirical analysis is going to be conducted using data which is pooled across product categories. In order to control for category-specific differences in price levels and average search spell duration we include a set of category fixed effects in all our regressions. In other words, we model how a consumer’s search activity within a category affects the particular product she buys from that category. In total, we have around 150 categories which are defined as groups of products that are naturally substitutes for each other but not with other

\[\text{\textsuperscript{12}}\text{The linkage between traffic- and product-points is provided in the data. Mostly any product location is associated with two or three traffic points. However, at a few special locations such as the end of an aisle more traffic points can be associated with a given product location.}\]

\[\text{\textsuperscript{13}}\text{Furthermore, we only observe the movement and stationarity of the cart, but not the consumer herself. To the extent that carts or baskets are left behind, this might also contribute to measurement error in the duration of stationary periods.}\]
products outside of the category. Examples for categories defined in this way are Bacon, Beer and Bird Food.

In order to quantify the possible benefits of search, we report the category-specific differences between the highest and the lowest price in the category. Because prices for the same product vary substantially over time, we compute the difference between the minimum and maximum price for each day/category combination. We then compute the average of this variable across days for each category. The first row in the bottom panel of Table 1 reports the distribution of the min-max price difference across categories. On average, there is a price difference of $4.21, but this difference varies across categories. At the 25th percentile, the price difference is equal to $1.78 and it rises to $5.26 at the 75th percentile. We also report the percentage difference of the lowest daily price relative to the highest daily price in the category in the second row of the same panel.

Because there is substantial variation in prices due to promotional activity, we also report some descriptive statistics on the time series variation in prices. For the purpose of this exercise we define a promotion as a daily price which lies at least 15 percent below the maximum price of that product over our sample period. Similar to the calculation for the price difference, we compute the share of promoted products for each day/category pair and then take the average across days for each category. The distribution across categories is reported in the third row. On average, about 30 percent of UPCs within a category are on promotion. Furthermore, even within our short time window many different products go on promotion. In order to capture this we compute the percentage of UPCs that went on promotion at some point during our sample period for each category. The average across categories is almost 60 percent which is substantially higher than the daily share of promoted products indicating that the identity of the set of promoted products changed frequently.

Taken together, the large within-category price dispersion as well as the substantial degree of promotional activity suggest that there are gains from search. The average category-level saving of $4.21 might seem relatively small compared to other (non-CPG) product categories, but relative to the amount of total shopping expenditure, it is not trivial. Consumers buy on average in 7 products categories on a shopping trip, which would allow for maximum savings of roughly $29. Furthermore, these gains can be realized by consumers on each shopping trip, i.e. on a very regular basis, and are therefore of a large overall magnitude.

3 Model and Identification Strategy

In this section, we outline the predictions of the canonical sequential search model described in McCall (1970) and describe how the model maps onto our specific context and data. In the sequential model, consumers receive draws from a distribution of utilities and optimally decide when to stop searching. In our context, consumers search across products within a category and we assume that they care only about price but not about other product characteristics. This simplification is motivated by the fact that we are not estimating the model structurally. We therefore choose a simple setup which is yet rich enough to illustrate the key aspects that
play a role in the identification strategy. Later, we extend the model to search over product characteristics other than price and analyze the implications of such a modified model. For now, we assume a consumer gets gross utility \( v \) if she consumes any product within the category. Further, the consumer incurs a search cost \( c_{\text{product}} \) when evaluating an additional product and receives a draw from the price distribution \( F(p) \) with support \([p, \bar{p}]\) for each search attempt. The optimal stopping rule is a time invariant threshold-rule \( \lambda \) (i.e. the consumer will accept any price below \( \lambda \)) which maximizes the consumer’s value function\(^{14}\)

\[
EV = -c_{\text{product}} + \int_p^\lambda (v - p) dF(p) + (1 - F(\lambda))EV
\]

Alternatively, one can interpret the optimal stopping rule as the value of \( \lambda \) which equates the marginal benefit with the marginal cost of searching

\[
\int_p^\lambda (\lambda - p) dF(p) = c_{\text{product}}
\]

One can easily see that the optimal threshold \( \lambda \) is increasing in search costs \( c_{\text{product}} \). Intuitively, a higher search cost will make the consumer less picky and therefore willing to accept a higher price.

In the standard search model, we can think of \( c_{\text{product}} \) as representing the cost of resolving uncertainty about one more option. However, in our data, we are not able to measure the number of options evaluated, instead we only know the extent of search activity measured in real time. In order to adapt the model to our setting, we model the search cost of evaluating one more alternative as \( c_{\text{product}} = \text{TimePerSearch}*c_{\text{time}} \), the product of time needed to search one option (\( \text{TimePerSearch} \)) and the opportunity cost of time (\( c_{\text{time}} \)). \( \text{TimePerSearch} \) represents the efficiency of the search process. It might (as any of the other model primitives) vary across consumers. For simplicity of exposition we ignore any consumer \( i \) subscripts. The conversion into real-time leads to a slightly modified optimality condition

\[
\int_p^\lambda (\lambda - p) dF(p) = \text{TimePerSearch} * c_{\text{time}}
\]

Using this condition it is easy to show that the expected price paid is equal to

\[
E(p) = \frac{1}{F(\lambda)} \int_p^\lambda p dF(p)
\]

and the expected number of searches is determined by

\[
E(N) = \frac{1}{F(\lambda)}
\]

therefore, the expected time spent searching is given by

\[^{14}\text{We ignore discounting due to the short amount of time that consumers spent searching in a given category in our data. We also assume that } v \text{ is high enough such that the consumer searches at least one option. We interpret this as the consumer being committed to buying in the category but deciding which specific product to pick from within the category.}\]
\[ E(\text{SearchTime}) = \text{TimePerSearch} \times E(N) = \frac{\text{TimePerSearch}}{F(\lambda)} \] (4)

Note that \( \lambda \) is the optimal stopping rule defined by equation (2) and is therefore a function of \( \text{TimePerSearch} \). A larger amount of time needed to make an additional search will increase search costs and therefore increase the stopping threshold \( \lambda \), making the consumer willing to accept higher prices.

Based on the relationships derived above, we can trace out how search-time and price paid change when varying the consumer’s search costs. Lowering search costs leads to a lower stopping threshold \( \lambda \) as determined by equation (2), which in turn increases expected search-time and decreases expected price (see equations (3) and (4)). The relationship is non-linear with extensions in search-time from a lower level being associated with larger gains in terms of finding lower prices. Moreover, the potential gains within a category are bounded by the lower bound of the price distribution. Figure (3) illustrates this relationship graphically. It is precisely this relationship between search-time and price paid that we aim to uncover. In other words, we want to quantify the impact of an additional second spent searching \textit{due to a lower search cost value} on price paid.

We re-iterate that because we do not structurally estimate the search model, its primary role is guide our thinking regarding identification. Most search models that we can think of generate a relationship between search-time and price paid when varying search costs as the one described in Figure (3). For instance a search model for differentiated goods where consumer are aware of brand-specific utilities but have to resolve uncertainty over price as in Honka (2014) (based on Weitzman (1979)) would also predict a longer search-spells and a lower price paid when search costs decrease. Similarly, a satisficing model as in Stütgen, Boatwright, and Monroe (2012) would lead to consumers evaluating more options and finding a lower price when their search costs are lower. Because the search literature features a multitude of different modeling approaches it is impossible for us to outline the implications of each approach in detail here. Most of the discussion on identification below however does not hinge on the model specifics. We therefore think of our model framework as the simplest one to illustrate the relevant aspects of the empirical strategy. The main shortcoming is that the model, for the sake of simplicity, focuses on price search. In a later section we extend the model to allow for search over other product characteristics. This aspect has important consequences for our estimation and we discuss it great detail later.

### 3.1 Identification

In line with the reasoning outlined above, one way to think about our empirical strategy is the following: If all the observed differences in search-time were caused solely by differences in consumers’ search costs \( c_{\text{time}} \), our data would trace out the relationship depicted in Figure (3). A simple OLS regression, possibly allowing for a non-linear effect, could be used in this case. As we outline in more detail below, there are likely to be factors other than search cost variation which affect search time (and price paid). The OLS estimate is therefore unlikely
to allow us to estimate the desired relationship.

In the absence of direct information on search costs, we need to find variables which are correlated with search costs and can thus be used as instruments. In other words, we need search cost shifters. In our baseline specifications, we use the consumer’s walking speed over the course of the trip, the total number of items purchased on the shopping trip, and a dummy for whether the consumer used a basket (rather than a shopping cart) as instruments for search-time. The identifying assumptions is that overall trip behavior such as walking speed and basket size is driven by exogenous variation in consumption needs and search-costs. For instance consumers might go shopping on the weekend where they are not in a rush. Such a trip would be characterized by a larger basket size and slower walking speed relative to a quick fill-in trip at lunch-time on a weekday. In other words, speed and our instruments are correlated because they are both affected by a latent third variable: search costs. As we argue in more detail below, our instruments only affect search-time due to their correlation with search costs but not any other factors affecting the search process.

In the following sections, we lay out the evidence in support of our exclusion restriction. In particular, there are several factor that will lead to bias in an OLS regression: (1) variation in category-level promotional activity over time, (2) the role of chance in the search process, (3) measurement error in search-time. We argue that none of these three factors is likely to be correlated with our instruments. The main reasoning with respect to all three confounds is that they constitute relatively localized factors which influence the category-level search process and the measurement of it. However, the typical search-spell last 10 seconds whereas the average trip duration is 23 minutes. We thus argue that trip-level characteristics such as the number of purchased items, walking speed and the choice to use a basket or cart are unlikely to be affected by factors which are specific to search within any particular category.

The main confound that our instruments might not fully address is a potential correlation between search time and price sensitivity. If more price sensitive consumers also have lower search costs we are likely to overestimate the effect of search on price paid. While search-time is conceivably correlated with price sensitivity, this is much less clear for our set of instruments. For instance, we do not have a strong prior as to whether consumers that purchase more items on a given trip are more or less price sensitive. Nevertheless, we later run several additional checks to probe whether heterogeneity in preferences over product characteristics other than price might cause bias in our estimate.

3.2 Category-level Price Variation over Time

Consumers form expectations knowing that prices vary both across products and over time. The latter dimension is particularly important in the grocery shopping context due to the presence of high frequency price movements. As was shown in Section 2.2, price reductions due to promotions are very common in our data. Both dimensions are embodied in the price

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\[^{15}\text{No paper that we are aware of has direct data on consumers’ search costs. A typical approach is to use a structural model in order to back out search costs under some set of assumptions. We do not take this approach here.}\]
distribution governing the expectation process \( F(p) \). On any given day \( t \), there exists a price distribution \( F_t(p) \) across products that is (in most cases) not known to the consumer but that will influence the length of the search process as well as the expected price. Formally, this situation corresponds to the threshold value of the stopping rule being determined by \( F(p) \) whereas the expected number of searches and the expected price are a function of \( F_t(p) \)\(^{17}\).

\[
E(p) = \frac{1}{F_t(\lambda)} \int_\lambda^p pdF_t(p)
\]

\[
E(SearchTime) = \frac{TimePerSearch}{F_t(\lambda)}
\]

Days with more promotional activity are characterized by a price CDF with more weight in the left part of the distribution. This leads to a lower expected search duration as can be seen from the equation above. The impact on \( E(p) \) is in principle ambiguous and depends on how the mass of the probability density function moves with respect to the threshold. When more products are promoted this will lead to more prices lying below \( \lambda \). However, depending on where those prices lie within the truncated distribution, the expected price paid will increase or decrease. With our data we are able to directly test whether changes in \( F_t(p) \) have any impact on search-time and price paid. We do this by regressing time spent searching (and price paid) on the fraction of products promoted within the category and a set of category fixed effects. Doing so, we find a negative and significant effect in both regression\(^{18}\).

This result shows that changes in the price distribution lead to a movement of price paid and search-time in the same direction\(^{19}\). This could potentially mask the negative effect of search-time on price that we are seeking to uncover. Put differently, our object of interest is the effect of extending search-time on the price a consumers obtains from a given price distribution. However, as the discussion above illustrates, the fact that the price distribution changes over time needs to be controlled for. We therefore need the instruments to be uncorrelated with promotional activity in the specific category. This is likely to be fulfilled

\(^{16}\)It could be known to the consumer in some circumstances such as information about promotions being available through feature advertising. We will address this issue later.

\(^{17}\)Strictly speaking both \( E(SearchTime) \) and \( E(p) \) are also still a function of \( F(p) \) which determines the optimal stopping threshold \( \lambda \).

\(^{18}\)More specifically, regress time spent searching (and price paid) by consumer \( i \) in category \( c \) on day \( t \) on the fraction of products promoted within the category and a set of category fixed effects as well as day fixed effects

\[
SearchTime_{ict} = \alpha * FractionPromotedProducts_{ict} + \xi_c + \delta_t + \varepsilon_{ict}
\]

\[
Price_{ict} = \tilde{\alpha} * FractionPromotedProducts_{ict} + \tilde{\xi}_c + \tilde{\delta}_t + \tilde{\varepsilon}_{ict}
\]

where \( \xi_c \) (\( \tilde{\xi}_c \)) denotes the category fixed effect and \( \delta_t \) (\( \tilde{\delta}_t \)) the day fixed effect. The predictions outlined above correspond to a negative coefficient \( \alpha \) in the first regression. The prediction for \( \tilde{\alpha} \) instead is ambiguous. Note that controlling for category fixed effects is important here as promotional activity and search might vary across categories for a host of other reasons. Table \( \text{B1} \) in the appendix, reports the results from both regressions. Note also that we are less concerned with measurement error in search-time in this regression as search is used as the dependent variable.

\(^{19}\)Note that although the impact on price is theoretically ambiguous we do find a significant negative effect of promotional activity in the regression.
as long as consumers do not have any price information before arriving at the shelf. Even if consumers obtain information about pricing from promotional flyers and/or in-store displays, the IV is only invalid in the case where consumers adjust their walking speed and/or basket size to the price information, which we don’t consider to be a likely scenario.20

3.3 Measurement Error

In our data we are able to measure time spent in the vicinity of the product category, which presumably is a noisy measure of actual category-level search activity. In particular, measurement error in search-time might arise for a variety of reasons: the consumer might be looking at other categories nearby, leave her cart behind, or simply spend part of the time engaging in search-unrelated activity. In other words we are not dealing with measurement error that arises simply from imperfections in the data recording process. Instead, search-time as recorded in the data can be seen as a proxy for actual search effort. As usual, the presence of this measurement error will lead to attenuation bias in an OLS regression setup. Given the nature of our data, this issue could potentially be quite severe. However, as just outlined, we think of measurement error as arising from localized and relatively isolated occurrences such as the consumer leaving the cart behind or contemplating a purchase in another nearby category. The measurement error is therefore unlikely to be correlated with the trip-level variables used as instruments.

3.4 Chance and Search Spell Duration

Finally, there is another issue, specific to our context, that might cause attenuation bias in a similar way as measurement error. A sequential searcher can be more or less lucky in how quickly she comes across a price draw which lies below her stopping threshold. However, the expected price conditional on having already searched a certain number of times remains unchanged. In other words, whether the consumer searched only once or 10-times, conditional on not having stopped yet, the expected price is always equal to the unconditional price expectation at the beginning of the search process:

\[
E(p|p_1 > \lambda, \ldots p_k > \lambda) = E(p) = \frac{1}{F(\lambda)} \int_{p}^{\lambda} p dF(p)
\]

where \(p\) denotes the price of the actually purchased product, \(p_1\) to \(p_k\) denotes the price draws for the \(k\) options searched so far (without having stopped). The intuition for this result can be easily obtained from the basic dynamic optimization problem in equation (1). As long

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20Note, that variation in pricing over time could in principle be exploited in order to study the search process. More specifically, search-time differences for consumers facing different price distributions can be informative about consumers’ stopping thresholds and therefore ultimately their search costs. However, we do not see a simple way to use this variation without employing a more structural framework that allows us to invert search-time differences into the implied stopping thresholds and therefore search costs. This is in principle feasible, but not the approach we are taking in this paper.
as prices above the threshold are drawn, the consumer always finds herself back in the same situation with an unchanged value function when making the decision to continue searching.

To fix ideas, assume that there is a set of consumers with identical search costs (in terms of both $c_{\text{time}}$ and $\text{TimePerSearch}$), and therefore identical threshold value $\lambda$. The actual duration of their respective search spells will in general be different although the expected duration is the same, and this difference depends entirely on the sequence of price draws they receive. Furthermore, consumers with longer spells will not pay different prices on average because the expected price conditional on the number of unsuccessful searches is the same as the unconditional expected price. This generates variation in the duration of search spells which is uncorrelated with price.

Remember that we want to find the effect of search-time on price caused by a change in search costs. In other words, we want to know how much less a consumer pays who searches more on average because she is pickier. Therefore, we want to get rid of the variation in search duration which is caused by similarly picky consumers being more or less lucky with their price draws. In a similar vein as measurement error, the chance-induced variation in search spell duration would bias the effect of search-time on price paid towards zero. It seems safe to assume that our instruments are not correlated with chance during the search process and the IV should therefore deal with this issue.

4 Main Results and Robustness Checks

In order to analyze the impact of search time on the price paid within a category we run the following regression

$$p_{ijt} = \beta \times SearchTime_{ijt} + \zeta_c + \varepsilon_{ijt} \quad (7)$$

Where $p_{ijt}$ denotes the price consumer $i$ pays for product $j$ which she purchased on day $t$. $\zeta_c$ denotes a category fixed effect, the subscript $c$ denotes the category which product $j$ belongs to. $\varepsilon_{ijt}$ denotes the error term. A full set of category fixed effects is used across all our specifications as we want know whether within a given category longer search leads to a consumer picking a lower priced product. We cluster standard errors at the customer-level to allow for an arbitrary within-customer correlation of the error terms.

A few comments are in order regarding the interpretation of the coefficient on search-time in a regression that pools observations across different categories. The discussion in the theoretical model was framed around search within one category, it is therefore reasonable to ask how to interpret the effect of search on price paid when this relationship might differ across categories. In terms of our model, differences in the estimated effect across categories could be due to either differences on the benefit side of search or differences in search costs. The former is driven by difference in the price distribution with benefits being larger in categories with high price dispersion. In order to illustrate the aggregation across categories, consider the relationship between search-time and price within each category as illustrated in Figure
Given the shape of this relationship, our linear estimate will recover the slope of the curve for the average consumer in the sample. Figure (4) illustrates the local, average nature of our estimate in more detail. In particular, the magnitude of our estimate depends on whether consumers in our data search relatively little (represented by the red scatter-plot) or a lot (the blue scatter-plot). In the latter case, the average consumer realizes more of the potential gains from search and the incremental benefit at the margin is smaller. We can therefore interpret our estimates as the average consumer’s marginal benefit from search or the unrealized potential gain from extending search by another second. We would expect a rational consumer to equalize the marginal benefits of search across categories. This implies that even if the shape of relationship between price and search differs across categories, the slope at the optimal stopping point will not. Therefore, differences on the benefits side will in general not lead to different effect magnitudes across categories. Cross-category heterogeneity in the effect could however arise due to search cost difference caused by differences in product locations and placement. For instance categories with more facings per UPC might have higher search costs because different UPCs are further away from each other. To the extent that this happens our estimate can be interpreted as an average treatment effect across categories. Note that we tried to estimate the effect of search on price for individual categories, but were unsuccessful due an insufficient number of observations per category. On the positive side, our estimates allow us to aggregate savings to the trip-level which would be difficult with estimates from individual categories.

Results using the regression presented in equation (7) are reported in Table (2). We start by running the regression by OLS, which yields a negative and significant coefficient of search time on price. The coefficient is equal to -0.0071, in other words, an additional minute spent searching would lower the price paid by about 40 cents. In order to deal with the various issues described in the previous section, we implement our IV-strategy. In the baseline regression we use the consumers’ walking speed over the whole trip as our instrument. This is our preferred specification as speed presumably most directly reflects the extent to which the consumer is in a hurry and therefore her search costs on the particular trip. With walking speed as an instrument, we find that the first stage coefficient, reported in column (2), is highly significant with an F-stat of 618.87. Column (3) reports the coefficient of the effect of our (instrumented) measure of search time on price. We find a negative and significant effect of -0.0376 which is substantially larger than the OLS estimate of -0.0071 showing that the issues described previously had a substantial impact on the magnitude of the OLS coefficient. Quantitatively, the point estimate of the IV corresponds to about a $2.2 drop in price paid for an additional minute of search. We will return to the interpretation of the effect magnitude in more detail.

Note that based on our model we think of the consumer as having rationally decided not to continue searching as the expected gains were lower than her search costs. Our estimate therefore represent the potential gains that the consumer optimally decided not to realize in the search process.

This logic is only true under the assumption that consumer have correct expectations about prices across categories. If consumer over or underestimate their benefits from search (due to incorrect price expectations) differentially across categories, this would lead to heterogeneity in the estimated effect.

We also tried to investigate heterogeneity across different groups of categories such as categories with high and low price dispersion. Again, we found that we did not have enough data to draw any reliable conclusions.
As outlined before, we think of walking speed as being reflective of the consumers underlying search costs. Apart from speed, we would also expect other trip characteristics to be correlated with consumers’ search costs which allows us to test the robustness of our results to alternative instruments. Specifically, we expect search costs to be lower on trips with a larger overall basket size as consumers are more likely to engage in such trips when they are under less time pressure. We operationalize this idea using two variables as instruments: the number of purchased items and a dummy for whether the consumer used a basket rather than a shopping cart. The first and second stage for this alternative specification are reported in columns (4) and (5) of Table [2]. Both instruments are significant and have the expected sign. The joint F-stat is equal to 63.37 and thus weaker than our specification using speed as an instrument. The second stage coefficient is equal to -0.0528 and statistically significant. Although larger in magnitude than the coefficient reported in our baseline specification in column (3), the two coefficients are not significantly different from each other.

In Table [B2] in the appendix we further explore specifications with alternative instruments. We report first and second stage results using each of the above instruments on its own as well as all three instruments from the previous specifications together. We also employ two further instruments which capture “trip size” in a similar vein as the number of items purchased and the basket dummy. In particular, we use the duration of the trip (in minutes) and the in-store walking distance from the beginning to the end of the trip. Both instruments predict search-time well and yield a similar second stage coefficient. Once we include them together with the other three instruments however, they become insignificant. In other words they do not provide much additional explanatory power. We also note that while the second stage coefficients are not significantly different from each other, the point estimates do vary somewhat in magnitude. Our baseline coefficient has the smallest magnitude among all specifications and we are therefore, if anything, likely to underestimate the impact of search.

As a further robustness check regarding our choice of instruments, we also run a specification in which we use the consumer’s walking speed in the minute preceding a specific item pick-up. Relative to the three instruments used previously, this instrument has the advantage that it varies over the course of the trip and therefore differs across item pick-ups on the same trip. This features will be useful for a robustness check later. However, the validity of the instrument hinges on a clear delineation of the actual search process around a particular pick-up. If the beginning of the search spell is defined incorrectly, we might capture some part of the search process in the speed measurement leading up to the pick-up. Any measurement error in search-time might therefore also affect speed. For this reason we consider this instrument to be potentially more problematic than our baseline trip-level speed instrument. Note that trip-level speed is calculated over an average total trip length of 23 minutes and is therefore unlikely to be affected by individual search-spells which last only about 10 seconds. When running the regression using speed before the pick-up as instrument, we obtain a highly significant first stage coefficient of -3.636 with an F-stat of 1401.99. This is stronger than our baseline instrument, presumably because speed prior to a pick-up varies across purchases
within a trip and because it is more predictive of search-time than speed over other segments of the trip. The second stage coefficient is equal to -0.0299 (standard error of 0.0066) and not significantly different from our baseline result.

Finally, we re-run our main specification, but change the dependent variable: Instead of price paid we use an indicator variable that is equal to one if the consumer picked a product that was on promotion. Note that the number of observations is smaller as we need to observe regular purchases of a particular product in order define when it went on promotion.\footnote{We define a promotion as a price reduction of at least 15 percent relative to the product’s base-price.} This is only possible if the product is purchased relatively frequently. As before, the instrument is strongly correlated with search-time with an F-stat of 529. The results differ slightly from our baseline first stage only due to the difference in the number of observations used.\footnote{We replicated the baseline regression using only the observations for which the promotion dummy is defined and find results that are not significantly different from the ones using the full sample. This reassures as that issues of sample selection are unlikely to contaminate the analysis.} In the second stage, the magnitude of the coefficient (standard error) on search-time, reported in column (6) of Table (2), is 0.0082 (0.0046), i.e. an additional minute spent searching increases the likelihood of finding a promotion by 50 percentage points \((0.0082 \times 60 = 0.492)\). This specification shows that our effect is not estimated from consumers with longer search spells buying products with lower base prices which are possibly of lower quality. Instead, it is the case that longer search spells make it more likely for a consumer to buy a promoted product.\footnote{It could be the case that product with different quality levels go on promotion more or less often. However, in our data, we find no relationship between base price (which is presumably reflective of product quality) and promotional frequency. To test this, we regress the fraction of days a product is promoted on the baseline price and a set of category dummies. The regression is run at the product-level for the set of 5,848 UPCs for which we are able to define the promotion dummy. The coefficient on the baseline price is very small and insignificant with a coefficient (standard error) of 0.0016 (0.0018).}

Next we use the sequential search model in order to systematically run through a battery of robustness checks. Despite the fact that we do not structurally estimate the search model, it nevertheless provides a natural starting point to guide the sensitivity analysis. In particular we consider how variation in each of the model primitives influences search-time and price paid as well as how it relates to the consumer’s walking speed and our other instruments. The search model is quite parsimonious, therefore the set of model primitives we have to consider is small and comprises the price distribution \(F_p\) and search efficiency \((TimePerSearch)\). We further investigate several extensions of the simple model: (1) a model where consumers have preferences over non-price characteristics and therefore search not only for a lower price, (2) deviations from rational expectations which influence the consumer’s perceived benefit from searching and (3) the scenario where consumers have information about prices before arriving at the category location in the store.

## 4.1 Search over other product attributes

One threat to the validity of our estimation lies in the fact that consumers are likely to not only consider price but rather search over a broader set of product characteristics. As products in most categories are quite differentiated and consumers presumably have heterogeneous tastes over product attributes it is natural to ask how this interferes with our analysis. In the search
model this would be captured by the product valuation term \( v \) becoming consumer/product-pair specific

\[
EV = -c_{\text{product},i} + \int_{\lambda}^{\infty} u_{ij}(u_{ij})dG_i(u_{ij}) + G_i(\lambda)EV
\]

where \( u_{ij} = (v_{ij} - \alpha_i p) \) denotes utility which is a function of both price and brand preferences. \( \alpha_i \) denotes the individual-specific price coefficient and \( v_{ij} \) represent the consumer specific valuation of product \( j \). \( G_i(u_{ij}) \) is the cumulative density function that describes the distribution of utilities across products for consumer \( i \). In this framework consumers will find higher utility products as they search longer. A higher utility could be achieved either by a lower price or by finding a product which is preferable along other product dimensions, i.e. that has a higher realization of \( v_{ij} \).

First, note that the presence of preferences over other product characteristics does not necessarily invalidate our analysis. For instance, consider the situation where price sensitivity and brand preferences are randomly distributed across consumers. The higher the weight on brand preferences (relative to price) the lower will be the effect of search-time on price, but, it does not introduce bias into our analysis. However, if preferences are correlated with search costs across consumers this could cause a problem for our estimation. For instance, one could imagine that lower income consumers have a stronger preference for lower prices relative to quality and also have lower search costs. These consumers would be searching longer as well as pick a lower price product from a given consideration set due to their preferences. More formally, this implies that \( c_{\text{product},i} \) and \( \alpha_i \) are negatively correlated across consumers. Such a correlation would lead to an upward bias (in absolute terms) in the effect of search-time on price. This issue is not specific to our setting and none of papers on consumer search that we are aware of allows for a flexible heterogeneity distribution in price sensitivity and search costs. For instance De Los Santos, Hortacsu, and Wildenbeest (2013) estimate a homogenous good search model where the price coefficient for all consumer is normalized to one. Honka (2014) explicitly discussed the fact that in her model heterogeneity in the price coefficient and search costs are not separately identified. Generally, like our paper the data used in those papers has been cross-sectional, thus making it difficult to disentangle search costs and preferences.

To deal with the issue of separating price sensitivity from search cost differences one would ideally want to observe the same consumer searching multiple times. Under the assumption that preferences are time-invariant, but search costs are not, one could then identify the effect of the latter by comparing search-spell length and price paid across purchases and searches of the same consumer. Unfortunately, such data is not available to us due to the short time window of our sample. Instead, we hope that our instruments provide a cross-sectional substitute for identification through panel data. This is a valid approach as long as our

\[\text{Note that the threshold now denotes the minimum utility level at which the consumer will stop searching. In the price search model the threshold denoted the maximum price at which to stop.}\]
instruments vary primarily within but not across consumers. To illustrate the idea, assume that all consumers have small and large basket trips, but average basket size does not vary across consumers. In this case our number of items instrument would randomly pick some consumers that happened to be on a large basket trip and others on a small basket one. The two groups would however not differ by their price sensitivity. We think that our specification using the number of purchased items and the basket dummy fares well in this respect. Both variables are likely to mostly vary within consumers as a function of consumption need and search costs. Even if average basket size differs across consumers, we see no particular reason why the across consumer variation would be correlated with price sensitivity. Our baseline speed instrument might be somewhat more problematic in this respect as speed might be correlated with age which is likely to also affect price sensitivity. The fact that results are similar to the basket size IV-specification is therefore reassuring.

To further probe the robustness of our results, we run two additional tests which leverage within consumer variation in our data. Although second best to having an actual panel of consumer search behavior, our data does provide us with a panel aspect along two other dimensions that was not available in previous research on consumer search. First, we do have a panel of about six weeks for the purchase data. Second, within a given trip (and occasionally across trips) we observe the same consumer searching and purchasing in multiple categories. The within-trip dimension thus provides us with repeated observations of search behavior for the same consumer albeit in different categories.

In order to exploit the panel variation in the purchase data in a simple way, we compute for every UPC/day pair, the percentile of each UPC's price in the respective categories (day-specific) price distribution. We then take the average of the price percentiles for all purchases we observe for the same consumer. This gives us a simple measure of consumer-specific price sensitivity. We then include this metric as an additional variable in our baseline IV-specification. We can only do this for the set of consumers for which we have multiple observations and loyalty card information that allows us to link multiple trips of the same consumer. This leads to a slight reduction in sample size. In columns (2) and (3) of Table 3, we report the first and second stage for our baseline specification using the smaller sample. We then re-run the IV with the additional price percentile control variable in columns (4) and (5). Doing so, we find that price sensitivity does not predict search-time and is insignificant in the first stage. The coefficient on walking speed hardly changes at all due to the additional control. In the second stage we find, unsurprisingly, that the consumer's average price percentile is a strong predictor for price paid. However, the coefficient on search-time remains almost unchanged. As the comparison with column (3) and our full-sample baseline regression in column (1) shows, the slight change in magnitude is primarily due to the change in sample size. We also computed the absolute and percentage difference of a UPC's price to the maximum price in the respective distribution in order to make sure that our result is not driven by the functional form of the price sensitivity variable. Using these alternative instruments yields

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28Because only a small set of cart and baskets is equipped with the RFID, the panel dimension does not extend to the search data.

29To avoid circularity we omit purchases from trips for which we measure search-time in the path-data.
very similar results to the price percentile control.

Next, we run a robustness check which controls for individual-specific differences in search and purchase behavior by including a set of consumer fixed effects. In this way we are only identifying the effect of search from within consumer variation in search time. However, it is important to note that we rarely observe the same consumer searching in the same category repeatedly. Most of the identification does in fact come from within trip variation in search behavior across different categories. Although we have a small number of consumer for which we observe multiple trips, this dimension does provide relatively little variation. In order to implement a regression with consumer fixed effect we therefore need an instrument that varies at a more granular level than the trip-level instruments used previously. To this end we use walking speed over the minute preceding a specific pick-up as an instrument in the fixed effect specification. This instrument allows us to use within trip variation in speed, but has some shortcoming, which we discussed in Section 4. The results from this regression are reported in columns (6) and (7) of Table 3. As a point of reference, we first run a specification without consumer fixed effects using the new speed instrument. In column (7) we then also include consumer fixed effects and find an effect of search-time on price paid of -0.0220 (standard error of 0.0072), which is similar to the results of our baseline specification.

This robustness check deals with preference heterogeneity only as long as a consumer’s price sensitivity does not vary across categories and trips, but search costs do. If instead consumers are more price sensitive in some categories than in others, for instance due to a stronger preference for quality relative to price in some categories, then consumer fixed effects might not fully address the issue. However, even if preferences were category specific, this would only be an issue if search-costs were also category specific in a way that creates a spurious correlation. I.e. categories in which consumers have stronger preferences over quality would have to be categories for which search costs are higher in order to overestimate the effect. Finally, due to the fact that we are mostly using within trip variation to identify the effect of search-time in this specification, one might wonder why search costs should vary at all over the course of the trip. While a more thorough discussion is outside of the scope of this paper, we note that we observe systematically shorter search spells toward the end of most trips, possibly suggesting that consumers might be less willing to process information and engage in search.

4.2 Price Distribution and Expectations

A model primitive that has a key influence on search behavior is the price distribution $F(p)$. We already discussed endogeneity concerns which arise from the fact that category-specific

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30 Note that the results in column (6) are slightly different from the ones reported for the “speed one minute before pick-up” instrument in the text in section 4. This is due to the fact that here we exclude consumers only one matched pick-up in order to keep the same sample as for the fixed effect specification.

31 Note that the number of observations for this robustness checks varies slightly relative to the baseline IV regression. This is due to the fact that we drop consumers for which only one item pickup is recorded when we include the fixed effects. We re-estimated the baseline model without the single-item trips (not reported) and find that the change in the sample size does not affect our results. For the same reason, the results in column (6) are slightly different from the ones reported for the “speed one minute before pick-up” instrument in the text in section 4.
price distributions vary over time due to the fact that different products go on promotion at different points in time. We now turn to two more issues related to the price distribution. First we consider the effect of consumers having biased expectations about the price distribution. Second, we investigate the consequences of consumers having information about daily prices, in particular promotions, before engaging in search. The latter is likely to arise in our setting due to the presence of feature advertising and in-store displays which provide price information to the consumer before she arrives at the shelf and starts searching.

4.2.1 Incorrect Expectations

A dimension in which consumers’ behavior might differ from the stylized model is in the way they form expectations about prices. As in any search model, expectations play a crucial role because they determine the marginal benefit of searching and therefore the optimal amount of search activity. In our search model, a deviation from rational expectations can be captured by the fact that the optimal stopping rule would be based on an incorrect price distribution. In other words, the optimal price threshold \( \lambda \) would solve

\[
\int_{\lambda}^{\infty} (\lambda - p) \tilde{F}(p) \, dp = c_{\text{product}}
\]

where \( \tilde{F}(p) \) represents the price distribution used to form expectations. In the case of non-rational expectation, \( \tilde{F}(p) \) will be different from the actual price distribution \( F(p) \). Note, that when the consumer engages in search, prices are still drawn from the true price distribution \( F(p) \), however the stopping threshold might differ from the one of a rational consumer. \( \tilde{F}(p) \) therefore only affects search-time and price via its impact on \( \lambda \):

\[
E(p) = \frac{1}{F(\lambda(\tilde{F}(p)))} \int_{\lambda(\tilde{F}(p))}^{\infty} p \, d\tilde{F}(p)
\]

\[
E(\text{SearchTime}) = \frac{\text{TimePerSearch}}{F(\lambda(\tilde{F}(p)))}
\]

It is easy to see that more pessimistic expectations will lead to shorter search spells as well as a higher expected price paid. The negative correlation between search-time and price that our estimation captures could therefore be in part due to heterogeneity in expectations across consumers. However, this is in fact ”good” variation rather than a confound that might interfere with the interpretation of our estimate. We re-iterate that expectations only influence search-time and price paid through their influence on the stopping threshold \( \lambda \). Moreover, the behavior of an overly optimistic consumer is observationally equivalent with the search behavior of a rational consumer with lower search cost. In other words, it is always possible to offset an increase in a consumer’s marginal benefit (due to over-optimism for instance) with

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\[32\] In virtually all structural models of search, consumers are assumed to know the the true price distribution. Indeed, imposing the expectation process is usually necessary for identification in any dynamic model, including models of search.
an increase in the marginal cost in such a way that the stopping threshold remains unchanged. This would lead to the same outcome in terms of expected price and search duration because price expectations and search costs only influence both price paid and search-time via \( \lambda \). For our estimation it matters little whether movement in \( \lambda \) originates from variation in search costs or expectations. More generally, any factor that influences the search process via equation (2), i.e. by altering the stopping threshold, but not equations (4) and (5) is unproblematic for our estimation strategy. On the contrary, it is precisely variation in the stopping threshold (for whatever reason) that we want to capture.

### 4.2.2 Information obtained before searching

Prices at the daily level are likely to be at least partially observed by some set of consumers due to feature advertising and in-store displays. This affects behavior in two ways. Consumers with prior knowledge about daily prices will base their expectations on this information whereas other consumers form expectations based on the distribution of prices over time and across products. This issue is very similar to the case of consumers having biased expectations. As discussed above, any type of variation in expectation formation does not cause any problems in terms of inference.

Apart from promotional activity having an impact on the set of prices being available and consumers’ expectations, it could also affect the probability with which a particular price is drawn. This is an issue specific to our setup because all product prices are visually "accessible" on the shelf. Promotions might therefore provide visual cues that draw the consumer’s attention to the promoted product. This could happen either because the consumer knows about the promotion and specifically tries to find this particular product or because promotional signs on the shelf capture her attention. Formally, such an effect would be captured by a shift in the CDF from which prices are drawn which would now assign more probability weight to products which are promoted on the particular day. This type of effect would lead to a negative correlation of promotional activity with search-time similar to the effect of variation in \( F(p) \) over time discussed earlier.

Our instrument is valid as long as prior knowledge of prices does not alter the consumers’ walking speed or basket size. Especially with regards to speed we think that our instruments are unlikely to be affected by prior price knowledge in individual product categories.

### 4.3 Differences in search-efficiency

The final model primitive whose influence on our analysis we need to look at is \( TimePerSearch \), the efficiency of the consumer’s search process. Most likely there is variation across consumers in how much time they need in order to resolve uncertainty regarding a specific number of options. The first order effect of a decrease in \( TimePerSearch \) is that it lowers the consumer’s walking speed or basket size.

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33Note that if there is any such variation in expectations in the data, our IV-strategy will most likely not make use of it. It does seem unlikely that consumers’ category-specific price expectations do influence their walking speed or basket size.

34In a pure price search model most typically the probabilities of drawing a particular price are uniformly distributed across products.
search cost and therefore leads to a lower stopping threshold $\lambda$. In other words, consumers who search more efficiently are willing to wait for a lower price draw as it is less costly for them to evaluate additional options in the search process. Search efficiency only affects price via this channel. However, the impact on search-time is more complicated. On the one hand, search-time will be longer due to the fact that a more efficient consumer is pickier, i.e. has a lower $\lambda$. At the same time, search-time is lower simply because it takes less time to evaluate an additional option. This is easy to see from equation (4), where $TimePerSearch$ enters in the numerator and $\lambda$ (which is a function of $TimePerSearch$) in the denominator. The consequences of variation in search efficiency for our estimation is similar in nature to a measurement error problem. Ideally, we would like to measure variation in the extent of search activity in terms of the number of options evaluated, but we only observe search effort in real-time. The total search duration can be decomposed into two components: the number of options evaluated and the time it takes to evaluate each option. The former has an impact on price paid, but the latter does not. Variation in search-time due to differences in search efficiency therefore cause attenuation bias in our estimate.

Because search efficiency is a latent concept, it is very hard to assess how much this issue could affect estimation. We are less sure in this case that our speed instrument is able to purge the problematic variation in search efficiency. It is conceivable that consumers who are less efficient when searching also generally walk at a lower speed. However, most likely $TimePerSearch$ is not correlated with the number of purchased items and the basket dummy, which we both use as alternative instruments. Our results, as shown in Table (2) as well as Table (B2) in the appendix, are robust to using those instruments instead of walking speed.

5 Effect Magnitude

We find returns from searching that are fairly large with roughly $2.20 per minute. However, because our measure of search-time is distributed with a mean of 10 seconds and a standard deviation of 8 seconds, a minute constitutes a strong linear extrapolation relative to the typical search time. In this section, we provide some guidance on how to interpret the magnitude of the effect.

By the nature of the search problem, the relationship between search-time and price paid is a non-linear one. Figure (4) illustrates this relationship when varying consumers’ search costs. The graph traces out how lowering search costs leads to a lower stopping threshold ($\lambda$) which in turn increases expected search-time and decreases expected price (see equations (2) to (4)). As the graph shows, extensions in search-time from a lower level are associated with larger gains in terms of finding a lower price. Moreover, the potential gains within a category are bounded from below by the minimum price within the distribution. Our linear estimate allows us to recover the slope of the curve in Figure (4) for the average consumer in the sample, the magnitude of which depends on whether consumers in our data search relatively little (represented by the red scatter-plot) or a lot (the blue scatter-plot). In the latter case, the average consumer realizes more of the potential gains from search and the incremental
benefit at the margin is smaller. Due to the local nature of the effect and non-linear shape of the relationship, we have to be careful not to extrapolate out linearly “too far”.

With this in mind, we use some back-of-the-envelope calculations in order to compute how large the gains from search can be within a given trip. Extending search-time by one standard deviation, i.e. by 8 seconds, lowers price by 30 cents. The average consumer purchases from 7 categories on a typical trip and could therefore save about $2.10 in total when extending search-time by one standard deviation in each product category. This constitutes roughly 8 percent of the average total shopping basket size of $27. Another way to quantify potential savings from search is to put them into the broader context of the total time budget allocated to the shopping trip rather than just the time spent searching. Consumers spent on average 23 minutes in the store and spent only about 80 seconds, i.e. 6 percent of their trip, searching. Extending search time by one standard deviation in each category, i.e. by 56 seconds, corresponds to a 4.5 percent increase in total shopping time and lowers expenditure by $2.10. Relative to the average trip-level expenditure of $27, this translates into an elasticity of expenditure with respect to shopping time of about -2 at the trip-level.

6 In-store Search and Product Location

In this section we explore how the estimates of search benefits derived above can be used to inform product location decisions as well as pricing as a function of product location. We think that in-store product location choice is a natural area to explore using a model of consumer search. In fact, if consumer did have perfect information about product characteristics and price, production location should matter very little. If instead consumer have to engage in costly search, then the store environment can be a tool to influence this process. Optimal store design is a complex problem and in its entirety outside of the scope of this paper. Nevertheless, we think that our estimates can be shed light on some aspects of product placement. Furthermore, this is a relatively under-researched area. Drèze, Hoch, and Purk (1994) is one of the few empirical papers on the effect of store layout that we are aware of. The advent of in-store tracking data such as the path-tracking data used here and in Hui, Fader, and Bradlow (2009), Hui, Bradlow, and Fader (2009a), Hui, Bradlow, and Fader (2009b) as well as video tracking in Jain, Misra, and Rudi (2014) should allow researchers to re-visit those important questions.

In order to gauge the potential for the store layout to influence search behavior we regress search-time on a set of dummies for different areas of the store. More specifically, we partition the store into 31 regions, which include aisles in the middle of the store as well as wall segments (of similar length as the aisles) along the perimeter of the store. Furthermore, we also partition each aisle in five roughly equally spaced segments. We use a set of dummies for the broad regions as well as a separate set for the within-aisle segments. Results from this regression are reported in Table 4. Due to the large number of regions we do not report the full set of

\[35\text{We did try to estimate the curvature of the relationship presented in Figures 1 and 4. When also including search-time squared, we find a negative coefficient on the linear and positive one on the squared term, which is consistent with the graph. However, neither coefficient is significantly different from zero.}\]
coefficients, but only some aggregate statistics on the coefficient values. We find difference in search-time across regions of up to 9.8 seconds as well as a maximum difference of 5.9 seconds between segments of an aisle. Search-time tends to be longer in the middle / bottom part of an aisle as well as in aisles towards the center of the store. Also, aisles generally see longer search-spells than walls at the perimeter of the store.

The question is whether we can attribute these difference in search-time to the physical location. Product categories are of course not located randomly throughout the store, and we might thus pick-up across-category differences with the location dummies. Second, it is possible that measurement error in the search-time metric varies across different areas of the store. The most likely reason for this to occur is that the probability of consumers leaving their cart behind might be higher in some areas than in others. We address the first issue by including a set of category fixed effects alongside the location dummies. The two set of dummies can be identified due to the fact that many categories are stocked in different areas of the store. Note that this is not an ideal control, because different locations for the same category are usually characterized by differences in product assortment. The first best would be to use panel data with changes in category location, but unfortunately our data does not contain such variation. To address the issue of measurement error we re-run the regression using only trips on which the consumer used a basket rather than a shopping cart. This mitigates concerns of locational differences in measurement error because consumers are presumably less likely to leave their basket behind relative to a cart. Regressions using category fixed effects as additional controls as well as results for a restricted sample of trips with baskets are reported in columns (2) and (3) of Table (4). Both specifications yields similar results to the specification in column (1). We note that both robustness checks have their limitations and we see the analysis in this section as more exploratory and suggestive. Ideally, one would randomly vary category locations over time and study the impact on search and purchase behavior. We leave such analysis to future research.

What do the difference in search behavior reported in Table (4) imply in terms of purchase outcomes? Using the regression results from our baseline regression, moving a product from the lowest search-time to the highest search-time location, both across and within aisles, implies a difference of almost 16 seconds which leads to a difference of $-0.590 = -0.0376 \times 15.7$ in terms of lower price which corresponds to roughly 20 percent of the median potential savings at the category-level (see Table (1)). Or, using the specification in column (6) of Table (2), a 13 percentage point increase in the probability of purchasing a promoted product.

---

36 We also tried including the number of UPC within each category/location pair and found that results are qualitatively similar.

37 Note that the specification using category fixed effects yields much larger standard errors. However, if anything results from this specification indicate an even larger difference in search-time across locations (relative to our baseline specification in column (1)).

38 A deeper question is why certain locations within the store see more search activity than others. We find in our data that consumers’ search-time varies systematically over the course of a trip with search-time being lower at the very beginning and end of a trip, suggesting that awareness and cognitive ability to process information might vary over the course of the trip. We conjecture that at least part of the locational variation is due to variation in when on their shopping trip consumers tend to reach a particular location. A more detailed exploration is outside of the scope of this paper.

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Unfortunately, our specification does not allow to translate the search-time differences easily into differences in terms of price elasticities. Nevertheless, the results suggest that locational factors do have a large impact on price sensitivity. This is relevant for manufacturers who pay slotting allowances to place their products in certain locations inside the store. Based on search-time difference some locations do engender closer competition with other brands due to consumers engaging in more search. Similarly, pricing decisions should arguably be a function of product location as well: In high search locations running a promotion will be more effective than in areas of the store where consumers’ search effort is lower.

7 Conclusion

We estimate the effect of search intensity on the price a consumer pays within a particular category using data from RFID tags on supermarket shopping carts. Recording search in a physical store environment is generally challenging and even our detailed data is only able to capture total search-time, but not which options the consumer evaluated. The technology does however have the advantage of not interfering in any way with the consumer’s natural shopping experience and might be the best possible way to gain insights into consumer search in a brick-and-mortar store. To the best of our knowledge this paper, together with Jain, Misra, and Rudi (2014), is the first to use direct data on search effort to analyze consumer search within a brick-and-mortar environment.

We employ a reduced-form approach to estimate the effect of search intensity on the price a consumer pays within a particular category. We find that an additional minute of search lowers expenditure by about $2.2. The gains from search are substantial, increasing search-time by one standard deviation in each purchased category leads to a 8 percent reduction in total shopping basket expenditure. This result is robust to a host of sensitivity checks which deal with possible confounds such as variation in prices over time, measurement error and correlation between price sensitivity and search costs. Due to the limited amount of observations per category in the data, our evidence comes from regressions which are pooled across categories. Going forward, with path-data over a longer time-horizon for only one category, it should be possible to model the search process in more detail (possibly by means of a structural model). In particular, our approach only looks at the effect on price paid and does not directly analyze the role of other product characteristics. We are therefore not able to make any statements about the effect of search on consumer utility. However, we believe that the effect of search-time on price is a dimension of the search process which is particularly relevant for informing optimal supply-side behavior.

Our findings imply that, due to the limited amount of search, the use of marketing tools such as feature advertising and in-store displays can be very effective. Furthermore, firm behavior that influences consumer search interacts in an interesting way with pricing decisions. Because more search makes finding a lower price or promoted product more likely, firms have an incentive to encourage search when running a promotion. Finally, we find that product

\[39\] The data and empirical approach could also be used to study seasonal variation in search behavior which
location can greatly influence consumer behavior due to differences in search intensity in different areas of the store. Generally, we think that the type of data and approach presented here opens the door towards studying issues of product location and store design in more detail.

(as posited by Haviv (2013)) might be a source of counter-cyclical pricing.
References


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<tr>
<th></th>
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<th>S.D.</th>
<th>P25</th>
<th>Median</th>
<th>P75</th>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
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<td>Speed (Feet per Second)</td>
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<td>2.00</td>
<td>2.18</td>
<td>2.39</td>
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<td>3</td>
<td>6</td>
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<td>Trip Duration (Minutes)</td>
<td>23.65</td>
<td>17.18</td>
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<td>Trip Distance (100 Feet)</td>
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<td></td>
</tr>
<tr>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Speed 60 Seconds Before Pick-up</td>
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<td>2.31</td>
<td>2.81</td>
</tr>
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<td>1.59</td>
<td>3.99</td>
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<td><strong>PRICE SAVINGS</strong></td>
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<td>Absolute Difference between Daily Min and Max Price</td>
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<td>1.78</td>
<td>3.21</td>
<td>5.26</td>
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<td>Percentage Difference between Daily Min and Max Price</td>
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<td>0.23</td>
<td>0.53</td>
<td>0.71</td>
<td>0.84</td>
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<td>0.17</td>
<td>0.17</td>
<td>0.29</td>
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<td>Fraction of UPCs promoted during the sample period</td>
<td>0.58</td>
<td>0.32</td>
<td>0.41</td>
<td>0.62</td>
<td>0.83</td>
</tr>
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Table 1: **Descriptive Statistics: Prices.** The unit of observation is a trip in the top panel and an item pick-up in the middle panel. Our sample consists of 13,112 trips and 34,103 pick-ups. The unit of observation in the bottom panel is a category. There are 153 categories in our data.
<table>
<thead>
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<th>Type of Regression</th>
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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
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<td>IV 2nd Stage</td>
<td>IV 1st Stage</td>
<td>IV 2nd Stage</td>
<td>IV 2nd Stage</td>
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<tr>
<td></td>
<td>Price</td>
<td>Search Time</td>
<td>Price</td>
<td>Search Time</td>
<td>Price</td>
<td>Promotion Dummy</td>
</tr>
</tbody>
</table>

| Search-Time        | -0.0071*** | -0.0376*** | -0.0528*** | 0.0082*    |          |          |
|                    | (0.0016)   | (0.0112)   | (0.0159)   | (0.0046)   |          |          |
| Speed              | -4.762***  |           |           |           |          |          |
|                    | (0.191)    |           |           |           |          |          |
| Number of Purchased Items |           |           |           |           | 0.181*** | (0.018)  |
| Basket             |           |           |           |           | -0.588*** | (0.164)  |
| Dummy              |           |           |           |           |           |          |

| First Stage F-Stat | 618.87 | 63.37 | 385.75 |
| Category FEs       | Yes    | Yes   | Yes    | Yes    | Yes    | Yes    |
| Observations       | 34,103 | 34,103 | 34,103 | 34,103 | 34,103 | 23,441 |
| Trips              | 13,112 | 13,112 | 13,112 | 13,112 | 13,112 | 11,031 |
| Consumers          | 8,318  | 8,318  | 8,318  | 8,318  | 8,318  | 7,247  |

Table 2: **Baseline OLS and IV regressions.** Standard errors are clustered at the consumer-level.
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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<tr>
<td></td>
<td>IV 2nd Stage</td>
<td>IV 1st Stage</td>
<td>IV 2nd Stage</td>
<td>IV 1st Stage</td>
<td>IV 2nd Stage</td>
<td>IV 2nd Stage</td>
<td>IV 2nd Stage</td>
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<td>Sample</td>
<td>Full Sample Customers</td>
<td>Repeat Customers</td>
<td>Repeat Customers</td>
<td>Repeat Customers</td>
<td>Consumer with &gt;1 Pick-up</td>
<td>Consumer with &gt;1 Pick-up</td>
<td></td>
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<td>Dependent Variable</td>
<td>Price</td>
<td>Search Time</td>
<td>Price</td>
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<td>Price</td>
<td>Price</td>
<td>Price</td>
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<tr>
<td>Search-Time</td>
<td>-0.0370*** (0.0112)</td>
<td>-0.0461*** (0.0144)</td>
<td>-0.0445*** (0.0141)</td>
<td>-0.0262*** (0.0060)</td>
<td>-0.0220*** (0.0072)</td>
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<td>Trip-level Speed</td>
<td>-4.814*** (0.243)</td>
<td>-4.813*** (0.243)</td>
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<td>Speed 60 Seconds Before the Pick-up</td>
<td></td>
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<td>Average Price</td>
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<td>2.2374*** (0.1452)</td>
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<td>Consumers</td>
<td>8,318</td>
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Table 3: **Robustness Checks: Price Sensitivity Controls and Trip Fixed Effect Regressions.** Standard errors are clustered at the consumer-level. Sample size changes due to the fact that we exclude trips with only one pickup when including trip fixed effects and price sensitivity is only defined for consumer with repeat observations in our data.
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<tr>
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### AISLE SEGMENTS

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<tr>
<td>Middle-Top</td>
<td>2.161***</td>
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<tr>
<td></td>
<td>(0.218)</td>
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<td>Middle</td>
<td>5.007***</td>
<td>5.013***</td>
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<td>Middle-Bottom</td>
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<td>Bottom</td>
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<tr>
<td></td>
<td>(0.256)</td>
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### STORE REGIONS

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<td>7.214***</td>
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<td>(4.704)</td>
<td>(14.317)</td>
<td>(0.765)</td>
</tr>
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<td>Difference Top2 - Bottom2</td>
<td>8.793***</td>
<td>12.895*</td>
<td>6.866***</td>
</tr>
<tr>
<td>Region FE Coefficient</td>
<td>(2.413)</td>
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<tr>
<td>Difference Top3 - Bottom3</td>
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<td>9.966**</td>
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<table>
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Table 4: **The Effect of Product Location on Search-Time.** Standard errors are clustered at the consumer level. A full set of store region dummies are included in all specification. The “store region” panel presents hypothesis tests for differences between groups of fixed effect coefficients at the top and bottom of the distribution of coefficient values in each specification.
Figure 1: **Data-Structure.** The picture illustrates a consumer traversing an aisle. Consumer location within the aisle is recorded on a grid of traffic points. Products are located at specific locations on the shelf, which are coded up as a grid of product points. Product points are matched to nearby traffic points. This allows to measure how long a consumer remained near the product when picking it up. The dashed black line denotes the consumer’s path when traversing the aisle.

Figure 2: **Search-Time Histogram**
Figure 3: **Relationship Between Search-time and Price Paid when Varying Search Costs.** The picture illustrates the relationship between expected price paid and search-time for varying levels of search costs. The relationship is non-linear with extensions in search-time from a lower level being associated with larger gains. Moreover the potential gains within a category are bounded by the lower bound of the price distribution.

Figure 4: **Estimated Local Average Treatment Effect.** The picture illustrates the local nature of the estimated search benefit. The relationship between expected price paid and search-time for varying levels of search costs is represented by the solid line. The relationship is non-linear with extensions in search-time from a lower level being associated with larger gains. Moreover the potential gains within a category are bounded by the lower bound of the price distribution. The magnitude of our estimate depends on whether consumers in our data search relatively little (red scatter-plot) or a lot (blue scatter-plot). In the latter case the average consumer realizes more of the potential gains from search and the incremental benefit at the margin is therefore smaller.
A Appendix

A.1 Linking Sales and Path Data

One of the interesting features of our dataset is the linkage of sales to trip records. As part of the RFID tracking process, the data reports when the consumer arrives at the checkout. Independently, the sales data also has a time-stamp for each shopper’s transaction at the checkout. Comparing the timestamp of a particular path with the sales data allows to define a set of “candidate” checkout product baskets that occurred at a similar point in time.\footnote{The path-data timestamp that record the arrival at the checkout can be noisy as the consumer will be stationary when standing in line at the cashier. Therefore checkout baskets within a certain time-window after the consumer became stationary in the check-out area qualify as possible matches.}

Matching which trip goes with which specific transaction involves considering the physical location (i.e., longitude = x and latitude = y relative to the store map) of all the UPCs in each candidate basket. Based on how many of those locations lay on the path we are trying to match, a score is created for the baskets and the highest scoring one is matched to the path.\footnote{The data provider did not disclose the precise algorithm to us.} The matches do not necessarily yield a perfect score as consumer might occasionally leave the cart and pick up an item. Because of this we might not see the path of the consumer going past a specific item, even if the item part of her matched purchase basket. In this case no information on search-time will be available for the particular item.

Finally, when recording the data the location of products within the store is established once at the beginning of the sample period. As it is to costly to continuously track product placement at a daily level, there is a (small) level of noise in the data. The big majority of products in the store do not move within the short time window of our data. However, some movement does occur, primarily due to special promotional displays (end of aisle displays for instance). Overall we (and the data provider) believe that this is a relatively minor issue regarding the quality of our data.
### Appendix: Tables

<table>
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<tr>
<th>Dependent Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share of Promoted UPCs within the Category</td>
<td>-0.965*</td>
<td>-0.563***</td>
<td>-0.188***</td>
</tr>
<tr>
<td></td>
<td>(0.542)</td>
<td>(0.147)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>Average of the Dependent Variable</td>
<td>10.322</td>
<td>3.268</td>
<td>0.894</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Category FEs</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Day FEs</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>28,603</td>
<td>28,603</td>
<td>28,603</td>
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</tbody>
</table>

Table B1: **The Effect of Category-level Pricing on Search.** Search-time at the item pick-up level is regressed on the number of promoted item within the category of the purchased product. No further control variables (other than the indicated fixed effects) are used.
### 1st STAGE
(DV: Search-Time)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed</td>
<td>-4.762***</td>
<td>-4.373***</td>
<td>-4.433***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.191)</td>
<td>(0.204)</td>
<td>(0.320)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Purchased Items</td>
<td>0.185***</td>
<td>0.135***</td>
<td>0.133***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.016)</td>
<td>(0.020)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Basket</td>
<td>-0.935***</td>
<td>0.503***</td>
<td>0.516***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.158)</td>
<td>(0.166)</td>
<td>(0.171)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dummy</td>
<td></td>
<td></td>
<td></td>
<td>0.050***</td>
<td>-0.006</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.004)</td>
<td>(0.026)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trip Duration</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.036***</td>
<td>0.006</td>
</tr>
<tr>
<td>(Units: Minutes)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.003)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Trip Length</td>
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<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>(Units: 100 Feet)</td>
<td></td>
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</tr>
<tr>
<td>F-Stat</td>
<td>618.87</td>
<td>108.26</td>
<td>34.95</td>
<td>198.64</td>
<td>173.45</td>
<td>119.77</td>
<td>134.19</td>
</tr>
</tbody>
</table>

### 2nd STAGE
(DV: Price)

<table>
<thead>
<tr>
<th>Coefficient on Search-Time</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.0344***</td>
<td>-0.0499***</td>
<td>-0.0997*</td>
<td>-0.0376***</td>
<td>-0.0584***</td>
<td>-0.0645***</td>
<td>-0.0377***</td>
</tr>
<tr>
<td></td>
<td>(0.0127)</td>
<td>(0.0159)</td>
<td>(0.0535)</td>
<td>(0.0112)</td>
<td>(0.0171)</td>
<td>(0.0205)</td>
<td>(0.0112)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Category FEs</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>34.103</td>
<td>34.103</td>
<td>34.103</td>
<td>34.103</td>
<td>34.103</td>
<td>34.103</td>
<td>34.103</td>
</tr>
</tbody>
</table>

Table B2: **Robustness Check: Alternative Instruments.** Standard errors are clustered at the consumer-level.