ESSAYS IN MICROECONOMICS

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ABSTRACT

This dissertation consists of three essays in applied microeconomics. Each essay explores a different issue of economic interest.

The essay in Chapter 2 describes an experiment designed to investigate if using assets with an intrinsic value that increases over time leads to persistent undervaluation in laboratory asset trading markets. This question has not previously been investigated by researchers. Results from ten sessions are reported. Three used assets with an intrinsic value that decreased over time. The results from these sessions are consistent with the findings by prior researchers who frequently observed price bubbles in laboratory asset trading experiments. The remaining seven sessions used assets with an intrinsic value that increased over time. In all these sessions trading generally occurred at prices below the asset's intrinsic value.

In Chapter 3, in an essay co-authored with Adrian Stoian, we study road running races. Tournaments, where ordinal position determines rewards, are an important component of our economy. By studying sporting tournaments, we hope to shed light on the nature of other economically significant tournaments where data may be less readily available. We separately quantify the sorting and incentive effects of tournament prizes by employing a novel two-part model which we apply to a unique data set of road running race results. We present a counterfactual example of how a hypothetical change in prizes would be predicted to change race participation and speed.

In Chapter 4, in an essay co-authored with Jedidiah Brewer and Joseph Cullen, we examine the combined effects of the locations and the brands of retail gasoline outlets in Tucson, Arizona on market prices. We apply an innovative approach to model the impact of competing gas stations that avoids limiting analysis to predetermined nearby locations. We show that increased brand diversity is associated with higher prices and that gas stations affiliated with mass-merchandisers and grocery stores reduce market prices by a larger amount and over a greater distance than other types of gas stations. We demonstrate that our conclusions are not sensitive to the choice of distance metric.

CHAPTER 1

INTRODUCTION

This dissertation consists of three essays in applied microeconomics. Each essay explores a different issue of economic interest. The first essay describes a laboratory asset trading experiment which results in persistent undervaluation. The second essay describes an analysis of road running races which measures the impact of prizes on race choice and race performance. The third essay describes an analysis of retail gasoline prices which measures the impact of gas stations' locations and brands on market prices.

Periods of sustained overvaluation or price "bubbles" in financial and other markets garner considerable academic, media and popular interest. Analogous phenomena have been observed in numerous asset trading experiments in the laboratory. Although it attracts less attention than price bubbles, investors in financial markets argue from time to time that particular securities or categories of securities are undervalued. Researchers have not systematically investigated undervaluation in a laboratory setting. The essay in Chapter 2 describes an experiment designed to test whether using a novel type of asset results in sustained undervaluation.

The type of asset generally used in asset trading experiments is expected to pay a positive dividend at the end of each trading period. This design feature has two ramifications. First, it results in the assets' intrinsic values declining over time as the experiment progresses since the holders of the assets can look forward to receiving fewer and fewer dividend payments. Second, liquidity increases over the life of the experiments since the intrinsic value of the assets decline and the amount of cash held by the participants increases. The novel type of asset used in the experiment described in Chapter 2 is expected to require a payment from the holders of the assets at the end of each trading period. As a consequence, the assets' intrinsic values increase over time (since as the experiment progresses the holders of the assets can expect to be required to make fewer and fewer payments). In addition, since the assets increase in value and the amount of cash held by the participants declines, liquidity declines over the life of the experiment.

Results from ten experimental sessions are reported. Three used conventional assets with an intrinsic value that decreased over time. The results from these sessions are consistent with the findings by prior researchers who frequently observed price bubbles in laboratory asset trading experiments. The remaining seven sessions used assets with intrinsic values that increased over time. In all these sessions trading generally occurred at prices below the assets' intrinsic values. Based on the observed results, the null hypothesis that the asset type had no effect on mis-pricing, or had an effect that was opposite in direction to that which was hypothesized, could be rejected at the 1% level.

Tournaments are characterized by rewards determined by ordinal position. In tournaments it is relative output, and not absolute output, that determines payment. Competitions of this type appear often in the economy. Examples include such diverse situations as promotions in corporations and universities, patent races, political elections, and sporting events. In Chapter 3, in an essay co-authored with Adrian Stoian, we study road running races. Our goal is to investigate whether race prizes have a measurable impact on the behavior of participants. To date similar studies of sporting tournaments have provided ambiguous results.

We propose a two-part model which enables us to separately quantify the effect of prizes on race choice (the "sorting" effect) and on race speed (the "incentive" effect). To the best of our knowledge, our method to separately model sorting and incentive effects is new. Using our methodology, we demonstrate that both sorting and incentive effects are present in the data set. We show that races with larger prizes are generally more attractive to potential participants and that this effect is most intense for the best runners. For weaker runners prizes are less important in determining race choice and for runners ranked below a critical point larger prizes reduce the attractiveness of a race. We show that on average, after controlling for other race and runner characteristics, runners run faster in races with larger prizes. Our findings are robust to a number of alternative specifications of our model. In order to illustrate the magnitude of the sorting and incentive effects we have identified, we present a counterfactual example showing how a hypothetical change in prizes would be predicted to change race participation and speed.

To suggest that the physical locations and the brands of retailers are important in consumer markets is unremarkable. As consumers we know that, all other things being equal, a conveniently located retailer of our preferred brand will be more attractive to us than one that is less easy to reach or is of a less appealing brand. However, depending as it does on the aggregate behavior of consumers and retailers, the combined effect of location and brand on market prices is complex. In Chapter 4, in an essay co-authored with Jedidiah Brewer and Joseph Cullen, we present a new approach to measuring the impact of retailers' locations and brands on market prices. Unlike prior researchers, we flexibly model the impact of competing retailers and allow the degree to which two retailers compete with one another to decline smoothly with distance.

We apply our novel approach to data from the retail gasoline market in Tucson, Arizona. In keeping with our goal of defining geographical market areas flexibly, we investigate three alternative metrics for measuring the distance between gas station locations: road distance; Euclidean distance; and, travel time.

We measure the impact of brand diversity on market prices. Theoretically brand diversity's impact is ambiguous. If consumers have preferences over brands, all else being equal, increased brand diversity will reduce the density of close substitutes, leading to increased equilibrium prices. However, if retail outlets of the same brand follow a coordinated pricing strategy then increased brand diversity may result in more intense competition and lower equilibrium prices. The net result from these two potentially offsetting effects is theoretically unclear and is a matter for empirical investigation. We show that in the Tucson gasoline market, increased brand diversity is associated with higher prices.

Our flexible approach to modeling geographic market areas is particularly appropriate for examining whether different categories of retailers have different impacts on market prices. We demonstrate that on average, gas stations affiliated with mass-merchandisers and grocery stores have a larger impact on prices over a greater distance than other types of gas stations. This suggests that the low-price strategy followed by these gas stations and the attractiveness of their affiliated stores intensifies price competition locally, leading to lower equilibrium prices over a wider area than is the case for other gas stations.

We show that our findings are not sensitive to the choice of distance metric and are robust to a number of alternative specifications of our model.

CHAPTER 2

IRRATIONAL GLOOMINESS IN THE LABORATORY

2.1 Introduction

Periods of sustained overvaluation or price "bubbles" in financial and other markets garner considerable academic, press and popular interest. In a closely scrutinized speech in 1996 the then Chairman of the Federal Reserve Board, Alan Greenspan, coined the phrase "irrational exuberance" to describe the behavior of financial markets in which prices substantially exceed fundamental values. Even though Chairman Greenspan's reference in his speech to irrational exuberance was brief, the financial markets listened, and irrational exuberance entered into the vocabulary of financial market commentators.

If market participants are at least sometimes irrational, why should they necessarily be exuberant rather than gloomy? Although it attracts less attention as a general phenomenon, investors argue from time to time that particular securities or markets are undervalued. In fact, much of what passes for analysis of individual stocks in the press and by investment banks is focused on identifying undervaluation. In addition, popular investment styles such as value investing are premised on the notion of finding shares that trade in the market at prices that are below their "correct" values. Given the widely held view that undervaluation exists in markets in the outside world, it seems worthwhile to explore whether persistent undervaluation can occur in a laboratory setting.

This chapter describes an experiment designed to investigate whether replacing the usual decreasing-value asset (which is known to be associated with bubbles in a laboratory setting) with one that increases in value over time changes the outcome of trading experiments in a systematic fashion. In particular, it was hypothesized that increasing-value assets might be associated with sustained undervaluation. In the face of increasing intrinsic values, backward looking participants may fail to upwardly calibrate their perceptions of value over time, increasing the chance for undervaluation to occur. In addition, increasing-value assets of the type used in the experiment reported here reduce liquidity over the life of the experiment, reversing the phenomenon of increasing liquidity built into most earlier experimental designs. If increasing liquidity is associated with bubbles it would seem plausible that decreasing liquidity might contribute to undervaluation.

In addition to examining the impact of different asset types (increasing-value and decreasing-value), the experimental design employed examines the impact of three different level of initial liquidity. From prior work, it is known that in conventional asset trading experiments higher initial liquidity is associated with bubbles. In an analogous fashion it would seem plausible that, in the case of increasing-value assets, lower initial liquidity might increase the tendency for trading to occur at prices below intrinsic value.

To the best of the author's knowledge, researchers have not previously investigated the impact of increasing-value assets of the type described here on laboratory asset trading markets.

2.2 Relevant Literature

There is a long and distinguished history of economists documenting and attempting to explain financial bubbles. For example, a classic book by Charles Kindleberger, *Manias, Panics, and Crashes: A History of Financial Crisis*, describes the recurring patterns of financial bubbles and crashes and includes references to similar studies.

The investigation of price bubbles in the laboratory began with Smith, Suchanek and Williams (1988). The experiments involved subjects trading assets in a continuous double-auction market. At the beginning of each experiment participants were endowed with units of an asset and cash. At the end of each trading period, each unit of the asset paid a dividend from a known distribution. Since after each period the number of future dividend payments fell, the asset's intrinsic value or "holding value" based on expected future payments decreased during the experiments.[1] At the end of the experiment, which usually occurred after about 15 trading periods, participants were paid in cash based on their closing balances. The authors found that in the majority of experiments with inexperienced participants prices exhibited bubbles relative to the asset's holding value. Typically a small number of trades below the holding value were followed by a more extended period of marked overvaluation and finally a rapid decline in prices to holding value by the end of the experiment. In the majority of the experiments reported in Smith, Suchanek and Williams (1988) subjects were undergraduate students; however, the

[1] In most experimental instructions the value of the asset based on its expected future payments is called "holding value." This term will be used in the remainder of this chapter.

results were broadly unchanged if undergraduates were replaced by professional business people.

Subsequent experiments have investigated the factors that support or hinder the development of price bubbles. For example, Caginalp, Porter and Smith (2001) examines price bubbles using a sealed bid-offer double-auction market (or call market) format. The authors found that bubbles are more likely to emerge if: (1) liquidity levels are high (i.e., the total value of initial cash endowments is high in comparison to the total holding value of the asset endowments); (2) dividends are paid each period and are available to purchase assets; and, (3) a closed order-book design is used (i.e., a trader does not see other traders' orders when she enters her own order).

A further example of investigators exploring the factors that encourage or hinder price bubbles in the laboratory is provided by Dufwenberg, Lindqvist and Moore (2005). In this paper the authors conclude that including even a minority of experienced traders substantially reduces the occurrence of bubbles.

Researchers have conducted asset trading experiments using assets with a constant holding value. For example, Noussair, Robin and Ruffieux (2001) describes an experiment in which the asset pays a dividend or requires the payment of a maintenance fee with equal probability. This arrangement results in the asset's holding value and the level of liquidity remaining constant during the experiment. The authors found that bubbles commonly occurred in this setting.

In what appears to be the first reporting of an experimental design that results in sustained undervaluation, Haruvy and Noussair (2006) reports results from laboratory asset trading experiments that allow for short selling. The authors find that if short-selling capacity is sufficiently large, trading frequently occurs at prices below the holding value.

2.3 Experimental Design

A 2x3 design was employed with the six treatments differing in the character of the asset being traded (decreasing-value or increasing-value) and the relative liquidity at the start of the experiment (high, medium or low). All the reported treatments consisted of 15 trading periods and included nine participants.

In the decreasing-value asset treatments the asset was similar to those used in most previous asset trading experiments. At the end of each period, each unit of the asset paid a dividend of 50¢, 30¢ or 10¢, or required a maintenance payment of 10¢, each with a probability of 25%.[2] Therefore with this asset type the expected outcome each period was a dividend payment of 20¢ for each unit of the asset. As a result, during the first trading period when there are 15 future dividends expected, each unit of the asset has a holding value of $3.00. Each period the holding value of the asset declines by 20¢ so that in period 15 it has a holding value of 20¢. For decreasing-value asset treatments, the decline in the holding value of the assets is matched by an increase in the expected

[2] In most prior experiments, only non-negative dividends were used. The possibility of a maintenance fee was included in the decreasing-value asset to improve comparability with treatments using the second asset type which required the use of maintenance fees and to check that the possibility of maintenance fees did not have an unexpected impact on the behavior of participants.

amount of cash held by the participants as a result of dividends they receive. Consequently liquidity, measured as the proportion of the total value of all participants' cash and assets (valued at the holding value) in the form cash, is expected to increase each period.

In the increasing-value asset treatments, at the end of each period the asset used paid a dividend of 10¢ or required the payment of a maintenance fee of 10¢, 30¢ or 50¢, each with a probability of 25%. In addition, at the end of period 15 each unit paid a liquidation payment of $6.00. In this case, the expected outcome at the end of each period was that a participant was required to pay a maintenance fee of 20¢ for each unit of the asset she held. As a result, the holding value of the asset increases by 20¢ each period, starting from a value of $3.00 in period 1. For increasing-value asset treatments, liquidity declines from period-to-period since the holding value of the assets increases and the expected amount of cash declines due to the payment of maintenance fees by participants.

In every treatment, based on the holding value, the value of each participant's initial endowment was $15.50 and the total value of the endowments of all nine participants was $139.50. In the high-liquidity designs, this total value comprised 18 units of the asset and $85.50 in cash. The corresponding numbers for the medium- and low-liquidity designs were 21 and $76.50, and 24 and $67.50, respectively. Table 2.1 provides a summary of the features of the six treatments included in the experimental design.

Table 2.1

Summary of the Six Treatments Included in the Experimental Design

Asset type D = decreasing I = increasing	D	D	D	I	I	I
Liquidity level	High	Medium	Low	High	Medium	Low
# participants	9	9	9	9	9	9
Total number of units of the asset	18	21	24	18	21	24
Total value of initial cash	$85.50	$76.50	$67.50	$85.50	$76.50	$67.50
Expected Liquidity[3]						
Period 1	61.3%	54.8%	48.4%	61.3%	54.8%	48.4%
Period 8	79.4%	75.9%	72.5%	43.2%	33.8%	24.3%
Period 15	97.4%	97.0%	96.6%	25.2%	12.7%	0.2%

As shown in Table 2.1, initial liquidity in the high-liquidity treatments was 61.3% and ending liquidity 97.4% or 25.2% depending on whether the asset was decreasing or increasing in value. The corresponding values for the medium-liquidity treatments were 54.8%, 97.0% and 12.7% respectively and for the low-liquidity treatments they were 48.4%, 96.6% and 0.2% respectively. By way of comparison, averaging over the five designs used in Smith, Suchanek and Williams (1988) yields average initial liquidity of 45.6% and average liquidity in period 15 of 80.4%. The designs most consistently associated with bubbles in Smith, Suchanek and Williams (1988), designs 3 and 4, had average initial liquidity of 49.8% and average liquidity in period 15 of 96.7%. Appendices A.1 and A.2 provide additional information about the initial endowments and liquidity trends of each of the six treatments.

[3] Liquidity is the proportion of the total value of all participants' cash and assets (valued at the holding value) in the form of cash. Since dividends and maintenance fees are stochastic in nature, actual liquidity beyond period 1 may differ from that indicated.

Each of the three decreasing-value asset treatments was conducted once. The main purpose of these sessions was to attempt to reproduce the results of prior researchers. These sessions were designated DH, DM and DL depending on whether liquidity was high, medium or low.

Seven sessions were completed using the increasing-value asset treatments. The three high-liquidity sessions were designated IHA, IHB and IHC. The single medium-liquidity session was designated IM and the three low-liquidity sessions were designated ILA, ILB and ILC.

The experiment was conducted using an adapted version of the MarketLink software first developed at the Economic Science Laboratory at the University of Arizona and now maintained by Georgia State University. All the changes made to the standard version of the software that is available for public use at the Econport website www.econport.org were designed to ensure that the information provided to participants on their computer screens was not misleading in light of the nonstandard asset type being used in the increasing-value asset treatments.

The experiment took place during April, May and June 2006 using computers at the Economic Science Laboratory at the University of Arizona in Tucson, Arizona. All participants were undergraduate students at the University of Arizona who had volunteered to participate in laboratory experiments by registering in an online recruitment database. On a random basis registered students were invited by email to take part in a particular session. Each individual participated in only one experimental session.

Following the participants' arrival at the laboratory they were registered and then provided with written instructions. Appendix A.3 includes an example of the experimental instructions. At the start of the session, participants were informed on their computer screens of their initial endowments of cash and units of the asset. Each of the 15 trading periods lasted for two minutes. Between each trading period was a 30 second review period. During trading periods participants could use their computers to participate in a continuous double auction trading market by entering bids (offers to buy) and asks (offers to sell) or accepting the outstanding bid or ask. No order book was maintained and any outstanding bid or ask was cancelled following a trade. Selling short and buying on margin were not permitted, although it was possible for participants to borrow to pay asset maintenance fees if necessary. On a continuous basis during the experiment participants were informed on their computer screens of their cash balances and asset inventory. In addition, they could see the outstanding bid and ask and the prices at which recent trades had occurred. At the end of each period participants were informed of the dividend or maintenance fee applicable to each unit of the asset and their updated cash balances. Each session lasted approximately one hour. At the end of each session participants were paid in cash in private an amount corresponding to their cash balances at the end of period 15 plus a show-up fee of $5. Including the show-up fee, the expected average earnings of participants was $20.50. Actual individual payments varied from under $6 to over $50.

2.4 Experimental Results

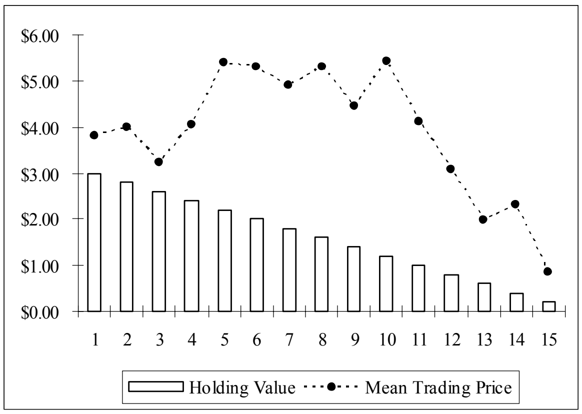
Summary period-by-period results for the first six sessions are shown in Figure 2.1. Figure 2.2 summarizes the results for the two additional increasing-value asset high-liquidity sessions and the two additional increasing-value asset low-liquidity sessions.

As can be observed from Figure 2.1, as expected decreasing asset values were associated with price bubbles. In the case of the increasing-value asset experiments, as shown in Figures 2.1 and 2.2, no price bubbles were observed and sustained undervaluation appears to occur. In addition, the graphical results suggest that increased liquidity may increase the extent of price bubbles in the decreasing-value asset treatments, while its effect in the increasing-value asset treatments is unclear.

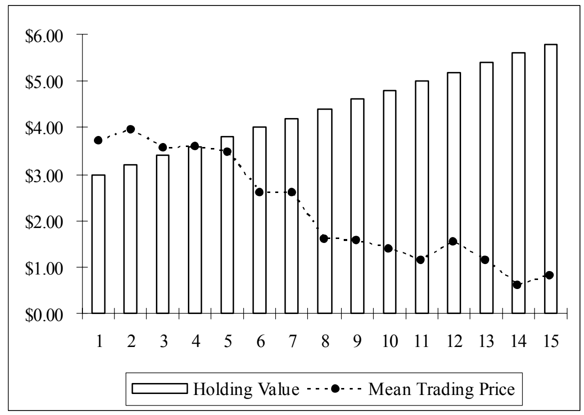
Figure 2.1

Summary Results for the First Six Experimental Sessions

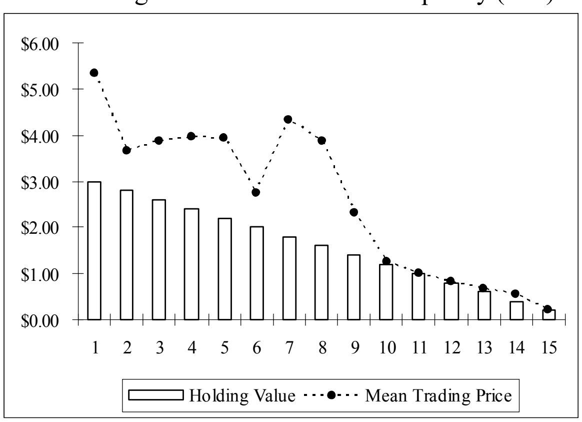
Decreasing-Value Asset High Liquidity (*DH*)



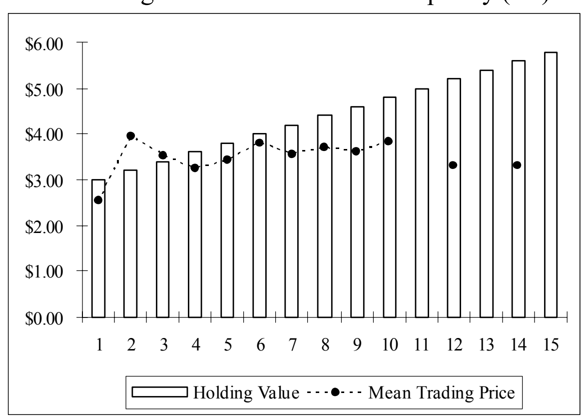
Increasing-Value Asset High Liquidity (*IHA*)



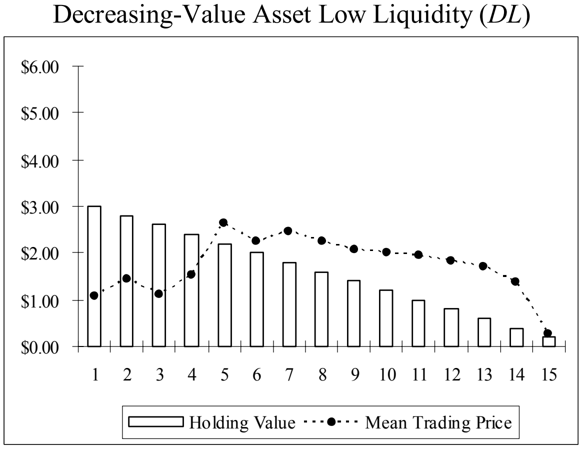
Decreasing-Value Asset Medium Liquidity (*DM*)



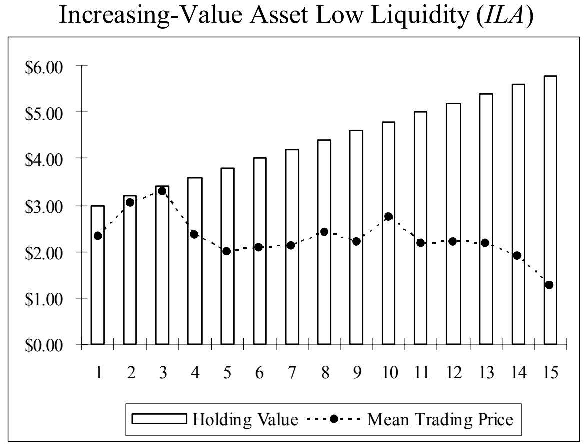
Increasing-Value Asset Medium Liquidity (*IM*)



Decreasing-Value Asset Low Liquidity (*DL*)



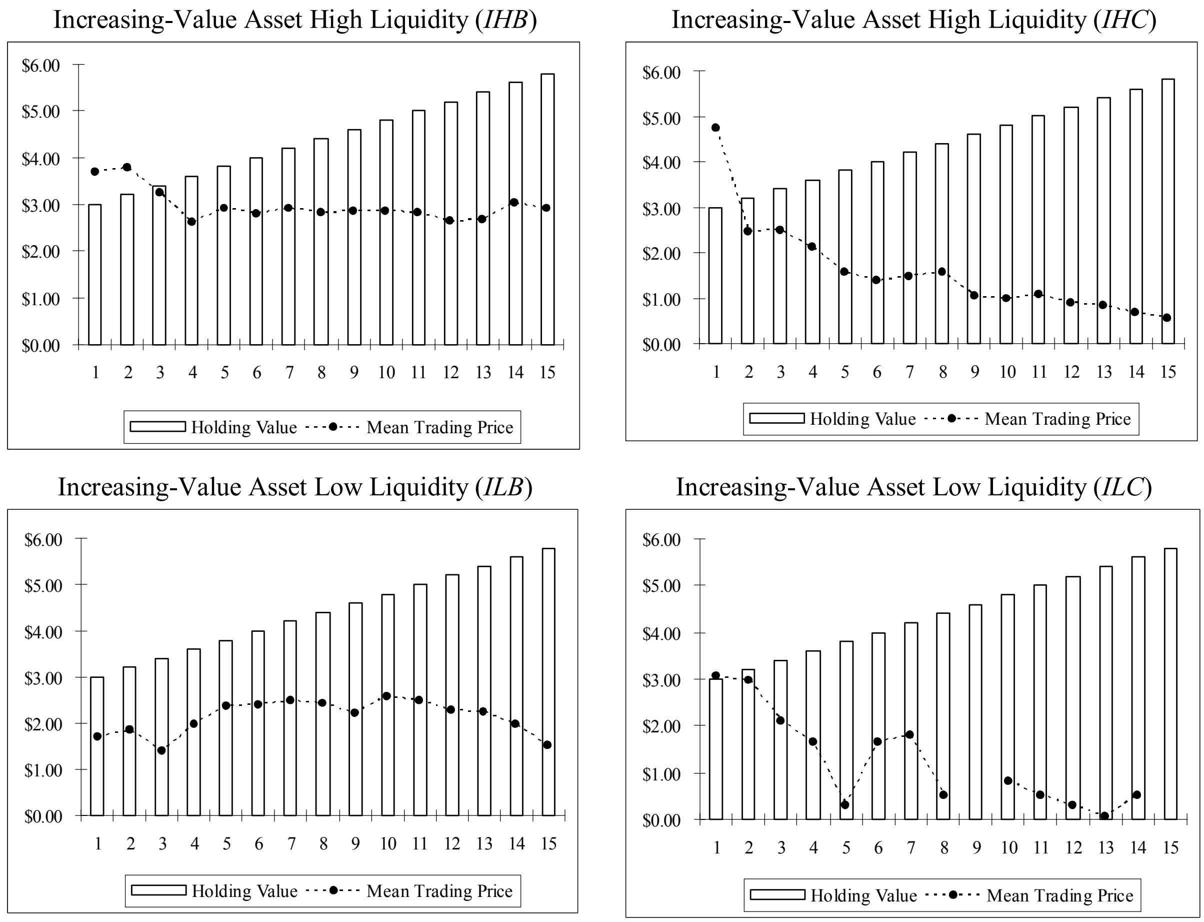
Increasing-Value Asset Low Liquidity (*ILA*)



Note: The absence of a point in a particular period indicates that no trades occurred in that period.

Figure 2.2

Summary Results for Additional Experimental Sessions



Note: The absence of a point in a particular period indicates that no trades occurred in that period.

Table 2.2 summarizes the degree of mis-pricing for each of the ten sessions using three alternative metrics. The first, mean excess pricing, averages the difference between the trade price and the prevailing holding value for all trades observed during an experimental session. The second, total excess pricing, multiplies mean excess pricing by the total number of trades in an experiment. The third, total excess pricing / unit, divides total excess pricing by the total number of asset units in an experiment.

Table 2.2

Observed Mis-Pricing for Each Experimental Session

Decreasing-Value Asset High Liquidity

DH	
Mean excess pricing:	$2.16
Total excess pricing:	$220.33
Total excess pricing/unit:	$12.24

Increasing-Value Asset High Liquidity

IHA	
Mean excess pricing:	-$2.00
Total excess pricing:	-$137.79
Total excess pricing/unit:	-$7.65
IHB	
Mean excess pricing:	-$1.21
Total excess pricing:	-$97.70
Total excess pricing/unit:	-$5.43
IHC	
Mean excess pricing:	-$2.92
Total excess pricing:	-$493.77
Total excess pricing/unit:	-$27.43

Decreasing-Value Asset Medium Liquidity

DM	
Mean excess pricing:	$1.00
Total excess pricing:	$124.74
Total excess pricing/unit:	$5.94

Increasing-Value Asset Medium Liquidity

IM	
Mean excess pricing:	-$0.40
Total excess pricing:	-$29.95
Total excess pricing/unit:	-$1.43

Decreasing-Value Asset Low Liquidity

DL	
Mean excess pricing:	-$0.06
Total excess pricing:	-$4.70
Total excess pricing/unit:	-$0.20

Increasing-Value Asset Low Liquidity

ILA	
Mean excess pricing:	-$1.71
Total excess pricing:	-$178.07
Total excess pricing/unit:	-$7.42
ILB	
Mean excess pricing:	-$2.05
Total excess pricing:	-$203.03
Total excess pricing/unit:	-$8.46
ILC	
Mean excess pricing:	-$2.36
Total excess pricing:	-$87.41
Total excess pricing/unit:	-$3.64

Reviewing the data in Table 2.2 it is clear that employing increasing-value assets is associated with undervaluation. By all three metrics the seven increasing-value asset sessions all display negative mis-pricing and have more under pricing than all of the three decreasing-value asset experiments. If in fact the asset type had no effect on mis-pricing with the observed outcomes being solely the result of random variations this outcome would be expected with a probability of 1/120. Therefore the null hypothesis that asset type has no effect on mis-pricing, or has an effect that is opposite in direction to that which was hypothesized, can be rejected at the 1% level.

With respect to liquidity the situation is less clear. By all three metrics the decreasing-value asset sessions show the expected ordering with increased liquidity resulting in more overvaluation. Although the small number of observations precludes drawing statistically robust conclusions, this result is consistent with the findings of Caginalp, Porter and Smith (2001). Turning to the increasing-value asset sessions, the impact of liquidity is ambiguous. As shown in Table 2.3 the ordering of the observations by the degree of mis-pricing varies depending upon which measure of mis-pricing is used.

Table 2.3

Ranked Mis-Pricing for the Seven Increasing-Value Asset Sessions

Session	Mean excess pricing	Total excess pricing	Total excess pricing/unit	Overall ranking
High liquidity				
IHA	4	4	5	5
IHB	2	3	3	2
IHC	7	7	7	7
Medium liquidity				
IM	1	1	1	1
Low liquidity				
ILA	3	5	4	4
ILB	5	6	6	6
ILC	6	2	2	3

1 indicates least undervaluation.
7 indicates most undervaluation.
Overall ranking is based on a simple average of the three mis-pricing measures.

If initial liquidity has no effect on mis-pricing in the increasing-value asset sessions, the mis-pricing rankings would be randomly assigned between the liquidity categories. As can be observed from Table 2.3 the null hypothesis that initial liquidity has no effect on mis-pricing in the increasing-value asset sessions can not be rejected.

Appendices A.4 and A.5 provide additional details concerning the experimental results.

2.5 Conclusions

The experimental design generally used in asset trading experiments in which the asset is expected to pay a positive dividend and has a known finite life has two unintended ramifications. First, it results in the asset's holding value declining over time since as the experiment progresses the holder of the asset can look forward to fewer and fewer dividend payments. Second, liquidity increases over the life of the experiment since the holding value of the assets decline and the amount of cash held by the participants increases. By employing an asset with different characteristics, the experiment reported here offers insights into the consequences of these experimental design features.

Which asset type (decreasing-value or increasing-value) is more "realistic" is debatable. On the one hand, in favor of the decreasing-value asset design, it could be argued that investment assets often pay dividends. On the other hand, in favor of the increasing-value asset design, investment assets are in fact usually expected to increase in value over time (or at least not decline in value). What is more, although investment assets often pay a dividend, it is not unusual to purchase these assets with borrowed money and if the interest paid to service the loan exceeds any dividend received a net payment is required from the owner. It is not necessary to resolve this issue. Since each design has some features that appear to correspond to real world circumstances (and each has simplifying unrealistic features), both would seem to justify study in an experimental setting.

Based on the results reported earlier, it is clear that increasing-value assets can be associated with persistent undervaluation in laboratory asset trading markets. It appears that the choice of asset type is an important experimental design choice that may have significant implications for the observed outcomes in asset trading experiments. In addition, the role of experimental design features such as inexperienced subjects and closed order books often loosely said to facilitate price bubbles is shown to require further clarification. Since the results indicate that these features can be associated with undervaluation as well as price bubbles, they might better be thought of as contributing to mis-pricing and not solely price bubbles. With regard to liquidity, in the case of increasing-value assets the results are consistent with initial liquidity having no effect on mis-pricing. Whether this is a consequence of the liquidity differences being too small to lead to distinguishable outcomes in this sample size or for other reasons is unknown.

Why does sustained undervaluation occur with increasing-value assets? As seems to be the case with price bubbles, it is likely that a number of factors are at work. Two possible contributing factors are: (1) the way in which participants develop their expectations about values may lead them to fail to upwardly adjust with increasing-value assets, increasing the chance for undervaluation to occur; and, (2) the low liquidity in the latter stages of all the sessions with increasing-value asset means that it is likely that participants have insufficient cash to purchase units of the asset at the holding value.

Relevant to how expectations might impact observed prices are findings by Haruvy, Lahav and Noussair (2006). In the case of markets prone to price bubbles, the authors conclude that inexperienced traders do not enter the market with expectations that prices will track fundamentals. Instead, they begin by expecting constant prices over time and later their predictions for future prices reflect a continuation of past trends. In the context of the increasing-value asset sessions reported here, participants that initially expected constant prices close to the starting holding value of $3.00 would after only a few periods have predicted prices well below actual prevailing holding values.

Table 2.4

Expected Average Cash per Participant / Asset Holding Value

Asset type D = decreasing I = increasing	D	D	D	I	I	I
Liquidity level	High	Medium	Low	High	Medium	Low
Period 1	3.17	2.83	2.50	3.17	2.83	2.50
Period 8	7.69	7.35	7.02	1.52	1.19	0.86
Period 15	75.50	75.17	74.83	0.67	0.34	0.01

With respect to the impact of liquidity, Table 2.4 shows the expected average amount of cash per participant divided by the asset holding value for each of the six treatments at periods 1, 8 and 15. It is clear from Table 2.4 that in the final trading period of the increasing-value asset treatments, on average, participants have insufficient cash to purchase the asset at prices corresponding to its holding value. This explains one difference between the results observed in the decreasing-value asset sessions and the increasing-value asset sessions. In the case of the decreasing-value asset sessions presented here and similar experiments reported by other researchers, prices return to close to the holding values in the final trading periods. No similar phenomenon is observed in the increasing-value asset sessions. In the final period of the increasing-value asset sessions, on average, participants have insufficient cash to pay the holding value for the asset and therefore if trading is to occur it must be at prices below the holding value.

Why are some participants prepared to sell units of the asset at low prices? Lei, Noussair and Plott (2001) call the wish to trade the "active participation hypothesis" and investigate it in the context of price bubbles. The authors conclude that much of the trading that occurs in experimental asset markets is due to the fact that participants wish to actively take part in the experiment and are offered no alternative activity to trading. The urge to trade and low liquidity could help explain the trading that occurs much below the holding value in the closing periods of many of the increasing-value asset sessions. Low liquidity and the active participation hypothesis would not seem to offer a full explanation for undervaluation that occurs during earlier trading periods where, on average, participants have sufficient cash to pay prices that correspond to the holding value. Perhaps lower liquidity and the different direction of change in liquidity (decreasing versus increasing) compared to decreasing-value asset sessions impact trading prices through some more subtle mechanism.

Further exploring the impact of initial liquidity and the possible contributing factors discussed above for the observed undervaluation in experiments with increasing-value assets may provide fruitful areas for further investigation. In particular, experimental designs that incorporate increasing-value assets without decreasing liquidity and designs with decreasing-value assets without increasing liquidity may make it possible to distinguish between the effects of asset type and liquidity trends that are intermingled in the treatments reported here. Decoupling asset type and liquidity trends could, for example, be achieved by attributing to each participant a known income or expense that is paid or charged each period unrelated to her asset holdings. In addition, experiments that would allow trading at the holding value in the final periods of treatments using increasing-value assets might be of interest. This could be done, for example, by endowing participants with a larger number (e.g., 100, 200 or 300 rather than 1, 2 or 3) of proportionately less valuable assets (e.g., assets with an initial holding value of 3¢ rather than $3). Finally, it may be of value to investigate design features that have been considered in the context of decreasing-value assets such as the degree of experience of the participants and whether order books are opened or closed in the new setting of increasing-value assets.

CHAPTER 3

THE SORTING AND INCENTIVE EFFECTS OF TOURNAMENT PRIZES[4]

3.1 Introduction

Tournaments are characterized by rewards determined by ordinal position: in tournaments it is relative output, and not absolute output, that determines payment. Competitions of this type appear often in the economy. Examples include such diverse situations as promotions in corporations and universities, patent races, political elections, and sporting events. In this chapter we study sporting tournaments where relatively rich data can be found. By doing so we hope to shed light on the nature of other more economically significant tournaments where data may be less readily available.

In general, tournaments are used as mechanisms to induce desired behavior by the participants. For example, promotion based on relative performance may serve to motivate employees to work hard, and prizes in sporting events based on competitors' finishing positions may motivate participants to train hard prior to an event and to exert effort in the event itself. In tournaments, prize values and structure are chosen by the tournament organizers in light of the organizers' particular objectives.

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[4] This chapter is co-authored with Adrian Stoian.

As discussed in Section 3.2.3, to date empirical studies of sporting events have provided ambiguous results. As a consequence, we are particularly interested in investigating whether tournament prizes have a measurable impact on the behavior of participants. This appears to be an important prerequisite if sports events are to offer an appropriate environment to test theories that may be applicable in other economically important situations.

Although there are a wide range of questions that researchers have considered concerning tournament design and the behavior of tournament participants, as a practical matter researchers have most often considered "within" tournament issues rather than "between" tournament issues. The focus has usually been on the incentive effect of prizes on the behavior of participants, assuming they are irrevocably committed to a particular tournament. In general, less attention has been given to the broader question of how participants sort into particular tournaments based on prizes and other tournament characteristics.

We propose a two-part model to examine the results from road running races which enables us to separately quantify the effect of prizes on race choice (the "sorting" effect) and on race speed (the "incentive" effect). The data set we use is unique and, unlike the data sets used in prior studies we are aware of, it includes runners that did not win prizes.

To the best of our knowledge, our method to separately model sorting and incentive effects is new. Using our methodology, we demonstrate that both sorting and incentive effects are present in the races we examine, and we are able to quantify their impacts.

3.2 Relevant Literature

We summarize below three categories of tournament research that are relevant to our investigation: (1) theoretical work; (2) experimental studies; and (3) sports-related empirical studies. Other research topics that use ideas from tournaments include patent races, executive compensation and promotions in corporations and universities.

3.2.1 Theoretical

Contrary to the impression that might be acquired by a casual reader of the empirical literature regarding tournaments, there is no single complete theory that can directly be applied to most real life tournaments observed in the economy. Instead a number of special theories with simplifying assumptions offer clues regarding the expected behavior of participants.

In Lazear and Rosen (1981) the authors show that a tournament can theoretically be superior to hourly wages by proving that, for risk neutral workers with uniform abilities, optimally structured tournaments yield results identical to piece rate pay and, if workers are risk averse, tournaments can be more efficient. The authors point out that they are unable to completely characterize the conditions under which piece rates dominate rank-order tournaments and vice versa. However, they do provide examples and observe that persons with more endowed wealth and smaller absolute risk aversion are more likely to prefer contests and those with low levels of endowed wealth and larger absolute risk aversion are more likely to prefer piece rates. The authors assume that the cost of effort is increasing and convex in effort. They argue that in the case of workers of heterogeneous ability it would be necessary to use credentials or other mechanisms to sort individuals into to the “right” contests if contests are to be efficient in the sense of participants choosing socially optimal levels of investment.

Krishna and Morgan (1998) consider the optimal design of tournaments for homogenous workers. Unlike many other papers that further develop the ideas from Lazear and Rosen’s pioneering paper, Krishna and Morgan focus on tournament design rather than comparing tournaments, piece rate pay or combinations of the two. The authors show that, regardless of risk preferences, winner-takes-all tournaments are optimal for up to three competing homogeneous workers. In this context optimal means the prize structure which induces the greatest total effort. In the case of four workers, the optimal structure of awards depends on the risk preferences of the participants. In the case of risk neutrality, winner-takes-all tournaments are again optimal. If workers are risk averse, the optimal tournament pays prizes to the winner and the runner-up. The authors assume that the cost of effort is increasing and convex in effort.

In Moldovanu and Sela (2001) the authors consider risk-neutral heterogeneous participants who differ in their cost of effort. In this context the authors show that winner-takes-all tournaments are optimal when the cost of effort is linear or concave in effort, while it may be optimal to have more than one prize if the cost of effort is convex in effort. The authors assume that ability is private information with abilities drawn independently from a known distribution. As in Krishna and Morgan (1998), optimal means the prize structure that induces the greatest total effort. Moldovanu and Sela’s assumption of privately informed heterogeneous participants and a deterministic relationship between effort and output contrasts with the papers discussed earlier where agents are identical and observed output is a stochastic function of unobserved effort.

In Szymanksi and Valletti (2004) the authors show that if output is a stochastic function of effort a second prize may be optimal if the contestants differ enough in ability. The authors show that in a three-person contest with one strong competitor and two equally weak competitors a second prize can be optimal from the point of view of eliciting maximum effort from every contestant. In this model whether or not a second prize is optimal depends on the difference in the cost of effort of the weak and strong players. The authors assume that the cost of effort is increasing and linear in effort and that participants are risk neutral.

Having surveyed some of the relevant theoretical literature, it is perhaps useful to assess how close the available models come to describing road running races. Table 3.1 lists in the left-hand column what appear to us to be the most salient characteristics of road running races. The remaining columns indicate whether or not the models developed in the theoretical papers reviewed in this section incorporate the relevant feature. As the reader can observe, there simply is no model that reasonably corresponds to road running races.[5] A similar gap between theory and the outside world exists with many other real

[5] Of course there are many other interesting theoretical papers discussing one feature or another of tournaments. Although we have not presented a full review of all these papers here we believe that our conclusion would hold even if this exercise was to be completed.

tournaments in the economy; often there is no appropriate theoretical model to be tested by empirical economists.

Table 3.1

Analysis of Selected Theoretical Models

	Lazear & Rosen	Krishna & Morgan	Moldovanu & Sela	Szymanski & Valletti
Large number of participants	No	No	Yes	No
Competition between tournaments not just within tournaments	No	No	No	No
Heterogeneous ability	No	No	Yes	Yes
Ability is public information	--	--	No	Yes
Output is a stochastic function of effort	Yes	Yes	No	Yes
Flexibility in the tournament organizers' objectives	No	No	No	No

Although it is obviously simplistic and fails to reflect fully all the features of the models considered, Table 3.1 suggests two challenges. First, there is a challenge for theoretical economists to develop a more comprehensive theoretical framework. Second, since no directly relevant model exists, empirical economists need to develop a way to organize the data produced by many real world tournaments in order to understand them better and to suggest likely areas for fruitful theoretical work. This chapter attempts to make a contribution in the second of these categories.

3.2.2 Experimental

In light of the complexity of many tournaments compared to the available theoretical models, experiments may provide a useful link between theory and real world tournaments.

Harbring and Irlenbusch (2003) investigate different tournament design alternatives along two dimensions: tournament size and prize structure. Participants have homogeneous costs of effort and a predetermined number of prizes are awarded to those choosing the greatest effort. The authors find that average effort tends to increase and variability of effort tends to decrease with the number of prizes.

Orrison, Schotter and Weigelt (2004) use an experimental design in which the cost of effort is homogenous and output is a stochastic function of unobserved effort. Prizes are awarded to a predetermined number of those achieving the highest output. The authors found that behavior was invariant to tournament size (i.e., behavior is the same for tournaments with two players and one prize and say six players and three prizes). If the number of prizes was varied for a given number of participants, effort changed little although there was some evidence of effort declining if the number of prizes was very high.

It would seem likely that further areas of experimental research would be fruitful. In particular, investigating additional characteristics listed in Table 3.1 might assist in the development of a more comprehensive tournament theory.

3.2.3 Sports Related Empirical Studies

The economics of sports has received significant interest from researchers. Szymanski (2004) provides an extensive overview of sports economics. Below we briefly review two pairs of papers in this area that are relevant to tournaments. Ehrenberg and

Bognanno (1990) and Orszag (1994) study professional golf competitions and Maloney and McCormick (2000) and Lynch and Zax (2000) study road running races.

Ehrenberg and Bognanno (1990) use data from professional golf tournaments in US in 1984. The authors' analysis is restricted to the top 160 money winners for whom the average score on all rounds during the year is available. The authors use these average scores as a proxy for each player's ability. Heterogeneity in the prestige of tournaments is accounted for by using a dummy variable for major tournaments. Controlling for the tournaments' characteristics, an individual's ability and the ability of other players, ordinary least squares analysis is employed to estimate the effect of total prize money on an individual's score. The authors find a negative coefficient for total prize money, which is larger if the analysis is restricted to those players that have been most successful recently.

Orszag (1994) generally follows the same methodology and uses data from professional golf tournaments in 1992. In contrast to Ehrenberg and Bognanno, Orszag finds the coefficient for total prizes to be insignificantly different from zero. Orszag advances a possible explanation for the difference in results by pointing out that the weather variable in Ehrenberg and Bognanno's study appears to be highly correlated with the total prize, suggesting that weather conditions could be measured with error. Orszag's results imply that prizes in a particular tournament have no significant impact on a golfer's scores in that tournament. As the author states; "Perhaps golf is not the ideal example to study tournament theory, or perhaps tournament theory does not elicit the desired incentive results." Although Orszag does not put it in these terms, our instinctive assessment is that at this level of competition, prizes do provide incentives to practice and to train in the time prior to a tournament; however they do not in general change an individual's performance in a particular tournament. If a player has honed his skills through extensive training, trying harder than usual in a particular tournament simply does not reliably improve his score. If this hypothesis is correct, an increase in prizes should improve an individual's scores in all tournaments and not just the one that increased prizes. In this case, if scores are better on average at tournaments with large prizes it is because the prizes attract better players, not because particular individuals perform better than usual.

Is the balance between the efficacies of training prior to a competition (which improves performance for a number of different tournaments) and effort in the competition itself different for road running races so that the incentive effect in a particular race is meaningful and can be measured? As is the case of golf, the conclusions to date that can be drawn from the literature are contradictory. In both Maloney and McCormick (2000) and Lynch and Zax (2000) the authors endeavor to separate the anticipated positive relation between prizes and performance into incentive and sorting effects.

Maloney and McCormick use data for runners who won prizes in races that took place in the southeastern US over the years 1987 to 1991. The theoretical model proposed as a starting point is Lazear and Rosen (1981) with two identical, risk-neutral competitors. Using time per mile as the dependent variable, the authors attribute the coefficient for the prize spread, defined as the difference between the prize won by each runner and the next lowest prize, to the incentive effect and the coefficient for the average prize to the sorting effect. On this basis the authors find both an incentive and a sorting effect.

Lynch and Zax use data from races organized in US and abroad in 1994. The authors show that without controlling for ability, runners seem to run faster if the prize difference is higher. In this context prize difference is defined to be the amount of prize money a runner would lose in a particular race if she finished one place below the position implied by her pre-race ranking rather than at the position implied by her pre-race ranking. The pre-race ranking was constructed using 1993 world road rankings. Once ability was taken into account using fixed effects or 1993 rankings, the coefficient for the prize difference that would measure the incentive effect is neither of the expected sign nor statistically significant for almost all distances analyzed. Since after taking ability into account the apparent incentive effect seem to disappear, the authors conclude "that races with large prizes record faster times because they attract faster runners, not because they encourage all runners to run faster."

To date, the results of sports related empirical studies are at best ambiguous in validating tournament theories. If sports tournaments are to be a useful testing ground for theory in this area a necessary prerequisite is that participants respond to the observed incentives. If participants do not respond to the observable financial prizes, tournament theories are not invalided, after all it may be the case that participants are responding to other less readily observed incentives such as prestige or derivative financial incentives (such as endorsement income). However, if participants do not respond to financial prizes, the usefulness of sports tournaments to test tournament theories that are important in other areas of the economy disappears. One of the goals of our research is to determine whether in the context of road running races financial prizes can be seen to impact race choice and performance. If so, this type of sports events may serve as a useful area for future theory testing. If not, it would seem unlikely that sports tournament of this type offer the hoped for advantages compared to testing the same theories in environments of more direct economic relevance.

3.3 Econometric Model

In our model we assume runners make three decisions. First, runners decide whether to race in a particular period. Second, if they choose to race, runners determine in which of the available races to participate. Third, once they know the other race participants, runners choose the effort to exert in their chosen race. For simplicity we assume that: (1) the first decision is based on idiosyncratic factors that are independent from any of the factors that impact the second and third decisions and the runners' performances in their chosen races; and, (2) the disturbance terms in the equations that describe the attractiveness of the races, the "sorting equation", (relevant for the second decision) and runners' performance, the "speed equation", (relevant to the third decision) are independent. Assumption (1) allows us to model just runners' second and third decisions. Assumption (2) simplifies the estimation of the sorting and speed equations.

As discussed in the next section, in our analysis we look only at "top runners", which we define as male runners who (1) finish in the top 30 in at least one race in our data set and (2) finish in the top 150 in at least one additional race in the data set.

For each race we identify up to two most closely competing races based on the date on which the races take place, the distance between race venues and the lengths of the races. In particular, the methodology to identify the most closely competing races used the following algorithm. First, only races occurring within a time period starting one weekend prior to the race of interest and ending one weekend after the race of interest were considered as candidate competing races.[6] Second, from the group of races occurring within the required time period we retained as candidate competing races only those races for which the venue was within 1,000 miles of the race of interest. Third and finally, from the remaining candidate competing races the two most similar in length to the race of interest were chosen. Applying this methodology to our data results in eight of the 71 races in our data set with top runner participation having no competing races, ten having only one competing race and the remaining 53 races having two competing races.

We assume that having decided to race in a particular period, a runner chooses between the race of interest and the most closely competing races only. If runner i has chosen to

[6] In the case of races that were half marathons or longer, this time period was extended to two weekends before the race of interest until two weekends after the race of interest. We believe that this approach is appropriate in light of the longer recovery time associated with races of this length.

compete in a particular period, the relative attractiveness of race k is A_{ik}. We assume that A_{ik} is determined as shown in Equation 3.1.

$$A_{ik} = x_k\alpha + r_i x_k \beta + \varepsilon_{ik} \qquad (3.1)$$

In Equation 3.1 x_k is a vector characterizing the prizes in race k and will include variables such as the total value of all prizes offered and the Herfindahl index of the value of the prizes offered, r_i is runner i's ranking and ε_{ik} is a disturbance term that accounts for a runner's idiosyncratic race preferences (i.e., preferences unrelated to prizes and ranking). For computational convenience we will assume that the disturbance term is i.i.d. extreme value. We assume that ranking is a measure of a runner's ability. The methodology we use to calculate each runner's ranking is based on a runner's success in beating other runners and is discussed in detail later in this section.

If a particular runner participates in race k rather than any of the most closely competing races which we designate $\tilde{k}$ then we know $A_{ik} \geq A_{i\tilde{k}} \ \forall \ \tilde{k}$. We define P_{ik} as the probability of observing runner i participating in race k rather than any of the most closely competing races. Since we are assuming ε_{ik} is i.i.d. extreme value we can use a logit model to calculate P_{ik} as shown in Equation 3.2.[7]

[7] As described in Appendix B.1, in some cases individual runners participated in one of the two competing races that had been identified. In this situation P_{ik} is defined as the probability that the relative attractiveness of the race the runner chooses not to participate in is less than the other two. If k and l are the races in which the runner participates and m is the one he does not, P_{ik} can be written as:

$$P_{ik} = \frac{e^{x_k\alpha + r_i x_k \beta}}{e^{x_k\alpha + r_i x_k \beta} + \sum_{\tilde{k}} e^{x_{\tilde{k}}\alpha + r_i x_{\tilde{k}} \beta}} \qquad (3.2)$$

Our estimates for the vectors α and β are the values that maximize the log likelihood function shown in Equation 3.3; this is the sorting equation.

$$L = \sum_{k}^{\substack{\text{all} \\ \text{races}}} \sum_{i}^{\substack{\text{all runners} \\ \text{in race } k}} \log P_{ik} \qquad (3.3)$$

For estimation purposes we parameterize the relationship determining the average speed for runner i in race k as shown in Equation 3.4; this is the speed equation.

$$speed_{ik} = W_k a + X_k b + Y_{ik} c + Z_i d + e_{ik} \qquad (3.4)$$

In Equation 3.4 W_k represents intrinsic race characteristics and will include variables such as race prizes, distance, distance squared, the topography of the race course and the prevailing temperature on the race day. X_k represents global competitive intensity and includes variables relating to the group of top runners participating in the race such as the total number of top runners in the race. Y_{ik} represents local competitive intensity and is related to the number of top runners competing in the race who are of similar ranking to the runner of interest. Unlike the earlier terms, this effect is specific to a particular runner in the race of interest. Our two measures of competitive intensity are designed to capture the intuition that individual effort (and therefore race speeds) will be influenced by the size and quality of the overall field and will also be impacted by the presence of runners

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$$P_{ik} = \frac{e^{-(x_m\alpha + r_i x_m \beta)}}{e^{-(x_k\alpha + r_i x_k \beta)} + e^{-(x_l\alpha + r_i x_l \beta)} + e^{-(x_m\alpha + r_i x_m \beta)}}$$

of a similar ability. Z_i includes personal characteristics of runner i such as ranking. The disturbance term, e_{ik}, is intended to reflect all other factors impacting a runner's speed and is assumed to vary by runner and race. We use ordinary least squares to estimate the vectors a, b, c and d.

As discussed in Section 3.2, some prior researchers have used ranking information that is intended to reflect a runner's ability as an explanatory variable. In the case of road running, rankings are not available for all the runners who are of interest to us, and therefore we are required to develop our own ranking system. For simplicity we assume that the relationship between rankings and the probability of one runner beating another does not depend on race characteristics.

Considering the top runners in our data set we have a total of 7,377 pairwise tournaments where we observe one top runner beating another in a race. Our goal is to assign a ranking to each individual that results in the fewest possible number of "wrong" predictions (i.e., the smallest number of cases where the lower-ranked runner beats the higher-ranked runner) and which assigns plausible rankings to groups of runners that never interact. The algorithm we used to determine rankings had two parts. First, initial rankings were calculated based on each runner's won/lost count which is equal to the number of pairwise victories minus the number of pairwise losses for each runner. Using the initial rankings calculated in this way, the number of pairwise tournaments in which the worse ranked runner beat the better ranked runner was calculated. Second, we tried to improve the initial rankings through an iterative search. One of the incorrectly forecasted pairwise tournaments was chosen at random and the rank of the loser reassigned to the winner and the ranks of the loser and all the runners with rankings between the original rankings of the winner and loser were demoted by one ranking. Using these revised rankings, the number of pairwise tournaments in which a worse ranked runner beat a better ranked runner was recalculated. If the number of incorrectly forecast pairwise tournaments was reduced the initial candidate rankings were replaced with the revised rankings. If the revised rankings did not reduce the number of forecasting errors the initial candidate rankings were not changed. Next another random draw from the incorrectly forecast pairwise tournaments based on the candidate ranking was taken and the process repeated. Using this methodology the initial proportion of incorrectly forecast pairwise tournaments was 13.7%. An iterative search consisting of 100 random draws reduced this to 12.0%. 500 draws reduced it to 8.0%. 1,000 draws reduced it to 5.9% and 5,000 draws reduced it to 5.1%. We used the rankings produced after 5,000 draws in our analysis.[8]

3.4 Description of the Data

Our data set was collected based on the information about races found in the *2002 Road Race Management Directory*. This booklet contains details about the most important road-race competitions that took place in 2002. We selected only the competitions for

[8] An example may serve to demonstrate why our methodology would not be expected to eliminate all incorrect forecasts. In our data no top runner competes with another top runner more than four times. There are seven pairs of runners that meet exactly four times. In the case of five of these pairs the same runner wins on each of the four occasions that they meet. For the remaining two pairs the results are not consistent. In these cases one runner wins on three occasions and the other wins on the fourth. In this small sub-sample there are a total of 28 pairwise competitions (four for each of seven pairs of runners). Given the inconsistent performances, rankings would fail to correctly predict the results of two of the pairwise competitions, corresponding to a failure rate of approximately 7%.

men held in United States that awarded monetary prizes for which we had a complete and accurate list of prizes and results. The results for each competition were downloaded from the competitions' official sites. Weather data were obtained from the Agricultural Weather Office at Clemson University. The characterization of courses in terms of topography (hilly, downhill or flat) was based on the way in which the race managers advertised their race in the *2002 Road Race Management Directory*.

As described in Section 3.3 we limit our analysis to what we term "top runners", defined as runners that finish in the top 30 in at least one race in our data set and in the top 150 in at least one additional race in our data set. We believe that these top runners are likely to be less subject to idiosyncratic reasons influencing race choice and race effort compared to less successful runners, and limiting our attention to these runners reduces computational complexity. This defines a revised data set consisting of 861 observations including 366 top runners in a total of 71 races. We observe a maximum of 42 top runners in each race and a minimum of one top runner. The maximum number of appearances by a top runner is six and the minimum two.

Summary information regarding the 71 races included in our analyses is shown in Table 3.2. The Herfindahl index of prize values provides a measure of the dispersion of prizes in a race and was calculated in the usually way by taking the sum of the square of the ratio consisting of the value of each prize divided by the total value of prizes. Consequently, this index takes values between zero and one with a value of one corresponding to a single "winner-takes-all" prize while lower values correspond to more widely dispersed prizes. In addition to the information shown in Table 3.2, 13 of the races were classified as hilly, five as down hill, 33 as flat and 20 as topography unknown.

Table 3.2

Summary Information by Race

Variable	Minimum value	Maximum value	Mean value
Total value of prizes ($000s)	0.05	30.25	4.68
Herfindahl index of prize values	0.14	1.00	0.34
Race distance (kilometers)	1.6	80.5	19.4
Average temperature (^{o} F)	35	84	62
Number of top runners	1	42	12.1

Additional information regarding the 861 observations included in our analyses is shown in Table 3.3.

Table 3.3

Summary Information by Observation

Variable	Minimum value	Maximum value	Mean value
Top runners within 20 ranking places	0	13	2.6
Ranking	1	366	176

A particular advantage of our data set over those used in the analyses that dealt with foot races in the context of tournament theory reviewed in Section 3.2 is that it permits us to observe the effects of prizes on athletes who did not win prizes.

3.5 Results

In this section we discuss the results of estimating Equation 3.3 (the sorting equation) and Equation 3.4 (the speed equation) and the robustness checks we performed.

3.5.1 Equation 3.3: The Sorting Equation

As shown in Appendix B.1, based on the algorithm we chose to identify competing races, out of the total of 861 observations 101 did not have any competing races and therefore 760 were suitable for use in estimating the coefficients in Equation 3.3. We first report results for estimating Equation 3.3 using a vector of variables to characterize race prizes (x_k) that contains the total value of all prizes and the Herfindahl index of the prizes offered. We chose to specify x_k in this way in the belief that prospective race participants might respond to both the overall purse of prize money and the manner in which it was divided between different prizes. The total value of all prizes and the Herfindahl index of the prizes appears to be a parsimonious way to capture these two features of the prizes offered in a particular race. Table 3.4 indicates the magnitude, standard errors and p values for the coefficients estimated using maximum likelihood.

Table 3.4

Sorting Equation Results

Variable	Coefficient	Standard error	p value
Total value of prizes ($000s)	0.1039	0.0298	0.000
Herfindahl index of prize values	-1.085	2.419	0.654
Rank x Total value of prizes ($000s)	-0.0003315	0.0001506	0.028
Rank x Herfindahl index of prize values	0.006923	0.010904	0.525

As can be observed from Table 3.4, it appears that in our data the total value of prizes and the total value of prizes interacted with a runner's rank are relevant to a runner's choice of race. The coefficients for both of theses variables are statistically significant at the 5% level. Neither of the coefficients relating to the variables including the Herfindahl index of prize values is statistically significant. The results from estimating Equation 3.3 using x_k consisting of only total value of prizes as shown in Table 3.5.

Table 3.5

Alternative Sorting Equation Results

Variable	Coefficient	Standard error	p value
Total value of prizes ($000s)	0.1101	0.0267	0.000
Rank x Total value of prizes ($000s)	-0.0003746	0.0001364	0.006

Now both of the relevant coefficients are statistically significant at the 1% level.

Based on the results of this second estimation, we can parameterize the expected attractiveness of race *k* to runner *i* as shown in Equation 3.5.

$$E(A_{ik}) = 0.1101(\textit{total value of prizes}_k) - 0.0003746(\textit{rank}_i \text{ x } \textit{total value of prizes}_k) \quad (3.5)$$

As expected, for highly ranked runners (i.e., runners with a ranking number that is low), increasing the total value of prizes offered increases the attractiveness of the race. For less highly ranked runners this effect is more muted. Using the point estimates of our results, we can conclude that the runner ranked 294th is indifferent to total prizes when choosing between races and for runners that are ranked below 294th increasing total prizes actually reduces the attractiveness of a race. Using the delta method we estimate the standard error for the point of indifference ranking to be 60 ranking places.

We explored the robustness of our reported results for the sorting equation by estimating a number of additional model specifications. First, we considered two alternative methodologies for determining competing races. Second, we added an additional explanatory variable corresponding to the number of other top runners actually observed to have participated in each race. Third, we re-estimated our original model using only observations where the runner was awarded a prize and observations where the runner failed to win a prize.

Table 3.6 compares our base case methodology for determining competing races with the two alternative methodologies.

Table 3.6

Comparison of Methodologies for Determining Competing Races

	Base case	Alternative 1	Alternative 2
1st selection criteria	Races occur +/- one weekend of race of interest (+/- two weekends for half marathons or longer)	Races occur +/- two weekends of race of interest (+/- three weekends for half marathons or longer)	Every race is assigned to one of 42 categories based on seven predetermined time periods, two predetermined geographical regions and three predetermined race length categories
2nd selection criteria	Race venue is within 1,000 miles of the race of interest	Race venue is within 800 miles of the race of interest	--
Final selection criteria	Choose up to two races most similar in length to the race of interest	Choose up to two races most similar in length to the race of interest	Choose up to two races from the same category as the race of interest based on the proximity of race venues

The sorting equation was re-estimated using the competing races produced by Alternative 1 and Alternative 2 summarized in Table 3.6. In both cases the two coefficients involving total value of prizes remained statistically significant at the 10% level and changed in magnitude by less than one standard error from the values reported earlier. In the case of Alternative 1 the two coefficients involving the Herfindahl index of prize values remained statistically insignificant. In the case of Alternative 2 these coefficients became statistically significant at the 10% level. The signs of the coefficients involving the Herfindahl index of prize values were unchanged by the choice of methodology used to determine competing races.

If the number of top runners was included as an explanatory variable the coefficient values and p values changed only slightly with the two coefficients involving total value of prizes remaining statistically significant at the 10% level while the coefficients involving the Herfindahl index of prize values remained statistically insignificant.

Of the 861 observations included in the data set used in our analysis, in 205 the runner was awarded a prize in the race of interest while in 656 he was not. We re-estimated the sorting equation using only the prize-winning observations and only the non prize-winning observations. In both cases the signs of the coefficients for the variables involving the total value of prizes did not change and the coefficients were statistically significant at the 10% level. As before, the coefficients for the variables involving the Herfindahl index of prize values were not statistically significant.

Further information regarding the results of the robustness checks involving the sorting equation are included in Appendix B.2. On balance the robustness checks support our choice of model specification described earlier.

3.5.2 Equation 3.4: The Speed Equation

The estimated coefficients for Equation 3.4 are shown in Table 3.7. The dependent variable used in the regression is average speed measured in units of meters per second.

Table 3.7

Speed Equation Results

Variable	Coefficient	Standard error	p value
W_k (intrinsic race characteristics)			
Total value of prizes ($000s)	0.00452	0.00286	0.117
Herfindahl index of prize values	-0.6479***	0.2139	0.003
Race distance in km	-0.03850***	0.00653	0.000
(Race distance in km)^2	0.0002657**	0.0001037	0.013
Dummy for hilly course	-0.1697***	0.0600	0.006
Dummy for down hill course	0.1117**	0.0462	0.018
Dummy if course topography unknown	0.02330	0.0813	0.775
Average temperature	-0.01638	0.02230	0.465
(Average temperature)^2	0.001478	0.0001962	0.454
X_k (global competitive intensity)			
Number of top runners	0.003715*	0.002164	0.090
Y_{ik} (local competitive intensity)			
Number of top runners within 20 ranking places	0.01877*	0.01061	0.081
Z_i (personal characteristics of runner)			
Runner ranking	-0.003458***	0.000135	0.000
Constant	6.516***	0.637	0.000

"*", "**" and "***" indicate statistical significance at the 10%, 5% and 1% level respectively.

The R squared for the regression is 0.83. Standard errors are adjusted for clustering by race.

The results for each component of the speed equation are discussed below.

W_k (intrinsic race characteristics): We find that prizes impact average speed, which is consistent with the direct incentive effect. Average speed increases with the total value of the prizes offered and as the Herfindahl index of prize values decreases. These effects are modest in size. An increase in total prizes by $10,000 is predicted to increase average

speed by approximately 0.05 meters per second.[9] A decline in the Herfindahl index of prize values by 0.25 (this could occur if a race organizer decided to double the total amount of prizes offered by awarding four equally sized prizes rather than two equally sized prizes) is predicted to increase average speed by approximately 0.16 meters per second. As expected, the magnitude and sign of the distance and distance squared variables indicate that average speed is predicted to fall with increasing distance with the rate of change declining as distance increases. For example, an increase in distance from 10 to 20 kilometers is estimated to reduce average speed by approximately 0.31 meters per second all other tings being equal while an increase in distance from 30 to 40 kilometers is estimated to reduce speed by only 0.20 meters per second. As indicated by the hilly course and down hill dummies, compared to a flat course a hilly venue reduces average speeds while a down hill course increases speeds. The dummy variable if course topography is unknown is not statistically significant. This dummy variable was employed if it was not possible using the information provided by race organizers to confidently categorize the race as hilly, downhill or flat. The fact that the coefficient is not statistically significant is consistent with the hypothesis that the races assigned to this category were not predominately of one type or another or that these unassigned races were in fact flat. The coefficients of the average temperature and average temperature squared variables are not statistically significant.

X_k (global competitive intensity): We used one variable in this category; the number of

[9] As an illustration, in race 8 (which is discussed in Section 3.6) the first top runner finished the 8 km course in 1,574 seconds. If this runner were to increase his speed by 0.05 meters per second his time would decline by 15 seconds; an improvement of 1%.

top runners participating in the race. The coefficient is statistically significant at the 10% level. As expected, as the number of top runners in a race increases so does average speed. All other things being equal, the results imply that a race with 10 additional top runners will have speeds that are approximately 0.04 meters per second faster.

Y_{ik} *(local competitive intensity):* After some experimentation we chose a single measure of local competitive intensity which appeared to have the greatest explanatory power: the number of competitors within 20 ranking places of the runner of interest. The estimated coefficient, which is statistically significant at the 10% level, indicates that a single additional runner close in ranking to the runner of interest is expected to increase his average speed by approximately 0.02 meters per second.

Z_i *(personal characteristics of runner):* Ranking is the only variable in this category. As expected, better ranked runners (i.e., those with lower ranking numbers) are predicted to run faster. All other things being equal the runner with ranking 1 is predicted to have a speed that is approximately 0.35 meters per second faster than the runner that is ranked 101. This coefficient is significant at the 1% level.

In order to investigate the robustness of our reported results, we estimated a number of alternative model specifications for the speed equation. First, we omitted runner rankings as an explanatory variable. This resulted in a substantial reduction in the reported R squared from 0.83 to 0.54. The reported coefficients for total value of prizes and Herfindahl index of prizes retained the same signs, were statistically significant, and were greater in absolute value than in our earlier analysis. These results are consistent with our assumption that ability is an important determinant of speed and that our rankings are a good measure of ability. As expected, the omission of a measure of ability reduced the model's explanatory power and upwardly biased the absolute values of the coefficient for total value of prizes since when rankings are omitted we fail to account for the fact that on average races with more attractive prizes include runners of higher ability. Second, we added two additional interaction variables to the model: runner ranking multiplied by total value of prizes and runner ranking multiplied by Herfindahl index of prizes. Neither of the new variables was statistically significant. Third we re-estimated the sorting equation using only the prize-winning observations and only the non prize-winning observations. Using only the prize-winning observations the coefficient for the total value of prizes was larger than in our base case analysis and was statistically significant at the 1% level. The coefficient for the Herfindahl index of prize values, the number of top runners and the number of top runners within 20 ranking places were no longer statistically significant. Using only the non prize-winning observations the coefficient values for the total value of prizes and the Herfindahl index of prize values were similar to those reported for the base case and both were statistically significant at the 10% level. The coefficients for the number of top runners and the number of top runners within 20 ranking places were both statistically significant at the 10% level. The results for the prize-winning and non prize-winning data are consistent with both groups responding to the total value of prizes with those who win prizes responding to a greater extent. While we can not reject the hypothesis that prize winners are insensitive to the dispersal of prizes and the other top runners in the race, non prize-winners appear to respond positively to more dispersed prizes, more top runners in the race and more closely ranked runners in the race. Fourth, we estimated a version of the model that excluded local competitive intensity. In this case the coefficients for the total value of prizes and the Herfindahl index of prize values were similar in magnitude to those reported for the base case and were both statistically significant at the 5% level. Fifth, we estimated the model with runner fixed effects. The coefficient of total value of prizes was statistically significant at the 1% level and was approximately unchanged in magnitude. The coefficient for the Herfindahl index of prizes was no longer statistically significant at the 10% level.

Further information regarding the results of the robustness checks involving the speed equation are included in Appendix B.3. Overall the robustness checks we undertook provide some additional comfort that the version of the model we presented earlier in this section is reasonable.

3.5.3 Choice of Ranking Methodology and Possible Endogeneity

Our methodology for determining rankings described in Section 3.3 uses runners' observed finishing positions. If Equation 3.4 correctly specifies each runner's performance, runner *i*'s speed and therefore finishing position in race *k* is influenced by e_{ik}. As a result e_{ik} impacts runner *i*'s ranking. But runner *i*'s ranking is included in Y_{ik} and Z_i in Equation 3.4 and so Y_{ik} and Z_i may be correlated with e_{ik}. Therefore as we have specified Equation 3.4, Y_{ik} and Z_i may be endogenous and consequently the coefficients we estimate for Equation 3.4 could be biased. This potential problem is partially addressed by the fact that the ranking for runner i depends not just on e_{ik} but on the disturbance terms for runner i in all the races he participates in our data set and indirectly on the disturbance terms for other runners. In addition, rank ordering may be less influenced by e_{ik} than would a continuous ability metric. The comparison of our base case results from estimating the speed equation with the fixed effect results leads us to believe that the possible endogeneity issue is not sufficiently large to place our qualitative conclusions in doubt. Notwithstanding this, a more detailed consideration of the potential impact of endogenous rankings seems worthwhile. If the rankings used in the speed equation were to be to endogenous, what would be the character of the endogeneity and can we predict its anticipated impact on our estimates?

Equation 3.6 is a simplified representation of the speed equation.

$$s = V\beta + e \qquad (3.6)$$

In Equation 3.6 s is a vector of the observed speeds, V is a matrix that includes all the variables that were shown as W, X, Y and Z in Equation 3.4 and e is a vector of disturbance terms. V includes rankings which may be measured with error. If so, we would anticipate the measurement error being inversely correlated with e since a runner that received a high draws of e may be assigned a better ranking (and thus a lower ranking number) than should be the case. If rather than using the true values of the variables, V, we actually use $\tilde{V}$, where $\tilde{V} = V + u$ and u is the measurement error, to estimate Equation 3.6, our estimate for β, $\hat{\beta}$, will be as shown in Equation 3.7.

$$\hat{\beta} = (\tilde{V}'\tilde{V})^{-1}\tilde{V}'s \qquad (3.7)$$

Substituting $s = V\beta + e$ and $\tilde{V} = V + u$ into Equation 3.7 yields Equation 3.8.

$$\hat{\beta} = \beta + (\tilde{V}'\tilde{V})^{-1}(V'e + u'e - V'u\beta - u'u\beta) \qquad (3.8)$$

Taking probability limits and recognizing that, since we can reasonably assume that V and e and V and u are uncorrelated, $p\lim\left(\frac{V'e}{N}\right) = 0$ and $p\lim\left(\frac{V'u\beta}{N}\right) = 0$ yields Equation 3.9.

$$\hat{\beta} = \beta + p\lim\left(\frac{\tilde{V}'\tilde{V}}{N}\right)^{-1}\left(p\lim\left(\frac{u'e}{N}\right) - p\lim\left(\frac{u'u\beta}{N}\right)\right) \qquad (3.9)$$

Since we only expect measurement error in the ranking measure and for simplicity ignoring any effect it could have via local competitive intensity, u is a matrix of zeros except for the column corresponding to rankings. Therefore $p\lim\left(\frac{u'e}{N}\right)$ is a column vector of zeros except for the element corresponding to runner ranking which has a value equal to the covariance of u and e. As discussed above, we would expect this covariance to be negative. Similarly, $p\lim\left(\frac{u'u\beta}{N}\right)$ is a column vector of zeros except for the element corresponding to runner ranking which has a value equal to the variance of u multiplied by the true coefficient for runner ranking. Thus we expect

$p\lim\left(\frac{u'e}{N}\right) - p\lim\left(\frac{u'u\beta}{N}\right)$ to be a column vector of zeros except for the element corresponding to runner ranking which will have a value equal to $cov(u,e) - var(u)\beta_{runner\ ranking}$. Since we expect $cov(u,e)$ and $\beta_{runnerranking}$ to be negative while $var(u)$ must be positive, without making further assumptions we do not know the sign of $cov(u,e) - var(u)\beta_{runner\ ranking}$. We can estimate $p\lim\left(\frac{\tilde{V}'\tilde{V}}{N}\right)^{-1}$ based on the observed values of the variables. Since only one element to the earlier vector is non-zero, only the column of $p\lim\left(\frac{\tilde{V}'\tilde{V}}{N}\right)^{-1}$ that corresponds to runner ranking can impact $\hat{\beta}$. These estimated values are shown in the first column of Table 3.8. The second column of Table 3.8 normalizes the values by dividing by the corresponding coefficient from Table 3.7.

The bias introduced to the estimates of each of the coefficients in the speed equation from the measurement error in rankings, *u*, and its correlation with the disturbance term, *e*, is estimated by multiplying the appropriate value from the first column in Table 3.8 by $cov(u,e) - var(u)\beta_{runner\ ranking}$. Since we do not know the sign or magnitude of $cov(u,e) - var(u)\beta_{runner\ ranking}$ we are stymied in predicting the direction and size of the bias for each coefficient. We are however able to predict whether or not pairs of coefficients will be biased in the same or opposite directions and from the second column of Table 3.8 we can see that on a relative basis the coefficient for total value of prizes is estimated to be the most biased.[10]

Table 3.8

Estimated Values from $\left(\frac{\tilde{V}'\tilde{V}}{N}\right)^{-1}$ Corresponding to the Column for Runner Ranking

Variable	Value	Value/est. coefficient
Total value of prizes ($000s)	0.0002659	0.0588
Herfindahl index of prize values	-0.005527	0.0085
Race distance in km	-0.0001009	0.0026
(Race distance in km)^2	-1.789E-07	-0.0007
Dummy for hilly course	0.0001877	-0.0011
Dummy for down hill course	0.001344	0.0120
Dummy if course topography unknown	-0.0009963	-0.0428
Average temperature	-0.0002865	0.0175
(Average temperature)^2	2.229E-06	0.0015
Number of top runners	-0.0001063	-0.0286
Number of top runners within 20 ranking places	0.0007415	0.0395
Runner ranking	9.859E-05	-0.0285
Constant	-0.006876	-0.0011

As an additional robustness check, we estimated both the sorting equation and the speed equation using alternative rankings based on the results of the speed equation using fixed effects. As before, rankings were assigned from 1 to 366. The runner with the highest dummy variable coefficient was assigned ranking 1 and the one with the lowest ranking 366. The average absolute difference between our base case rankings and the alternative

[10] Although we are not able to calculate the direction and magnitude of the bias, plausible “guesstimates” suggest that it could be relatively modest in size. For example, if we assume that the correlation coefficient of u and e is -0.1, the standard deviation of u is 20, the variance of e is equal the MSE in the base case estimate of the speed equation (0.27307) and $\beta_{runnerranking}$ is equal to the coefficient for runner ranking in the base case estimate of the speed equation (-0.003458), the implied bias for the coefficient for total value of prizes is positive and corresponds to approximately 2% of the estimated value.

ones based on the fixed effects analysis was 45. The model $fixed\ effects\ ranking_i = base\ case\ ranking_i + \varepsilon_i$ had an R squared of 0.65. Using the fixed effects rankings in the sorting equation yielded results that were similar to those reported earlier. As before, only the coefficients involving the total value of prizes were statistically significant. These coefficients were of the same sign and similar magnitude to those obtained using the base case rankings. Estimating the speed equation using the fixed effects rankings resulted in the coefficient of total value of prizes being statistically significant at the 5% level and of the same sign and similar magnitude to the base case. The coefficient for the Herfindahl index of prize values was no longer statistically significant. For completeness we also estimated the sorting equation using the estimated values of the fixed effects dummy variable coefficients in place of rankings. The results were consistent with those reported earlier with only the coefficients involving the total value of prizes being statistically significant. Further details of the results obtained by estimating the sorting and speed equations using the fixed effects rankings and the sorting equation using the fixed effects dummy variable coefficients in place of rankings are included in Appendix B.4.

Some discussion about why we prefer our base case formulation of the speed equation to one using fixed effects analysis is warranted. As discussed above, we have used the fixed effect analysis as a robustness check. As such it offers additional support for our conclusions. However, we believe that our base case approach that uses rankings based on the observed outcomes of pairwise tournaments is more useful. First, as we have constructed it rankings are needed in the sorting equation and they allow us to create a measure of local competitiveness for use in the speed equation: we believe these to be worthwhile contributions. Second, using rankings allows between runner comparisons to contribute to the estimation of the coefficients in the speed equation. This might be particularly useful if there is little observed variation in some variables within runners. Third, a continuous measure of ability based on the estimated values of the coefficients of the runner dummies from the fixed effects analysis would be endogenous and, as is usually the case with fixed effects, the estimated values would not be consistent. Fourth, although rankings based on rank order using the estimated runner dummy coefficients might help address the endogeneity issue (this requires the disturbance terms to be small compared to the differences between the fixed effects dummy coefficients), we believe that our approach for rankings is more robust. For example, by using between runner comparisons our ranking approach is less likely to be distorted if runners had preferences for unobserved characteristics of the races that influenced race speeds. In summary, we believe using rankings is beneficial and that our ranking approach reduces some of the shortcomings that arise if rankings based on the results of a fixed effects analysis are employed.

3.6 Counterfactual Analysis

In order to illustrate the expected impact of changing race prizes we consider the predicted result of a hypothetical change in the prizes offered in race 8. This race was chosen since it has only one competing race (race 28) and has only a limited number of top runner participants (five). These characteristics make the arithmetic for calculating the expected consequence of changing prizes a little easier than it would be for other races. The principles that would need to be applied are the same in all situations, including those where there are two competing races and where the number of top runners is large. Race 8 and race 28 are of the same distance (8 kilometers), occurred on the same day (June 16, 2002) and took place at relatively nearby venues (Boston in the case of race 8 and New York City in the case of race 28). The actual prizes for race 8 and the hypothetical revised prizes are shown in Table 3.9 along with the corresponding prize attributes that are relevant to Equation 3.2, and Equation 3.4.

Table 3.9

Actual and Hypothetical Prizes for Race 8

	First prize	Second prize	Third prize	Fourth to eighth prizes	Total prizes	Herfindahl index
Actual	\$150	\$75	\$50	\$25	\$400	0.2109
Hypothetical	\$1,500	\$750	\$500	\$250	\$4,000	0.2109

Using the coefficients estimated earlier as shown in Equation 3.5 and employing Equation 3.2, we are able to calculate the unconditional individual probabilities of each of the 18 top runners who actually participated in race 28 of having chosen to participate in race 8 at the actual prizes and at the hypothetical prizes. For runner *i* these probabilities are represented by p_a and p_h respectively. If runner *i* ranks above the level for indifference to prizes (estimated at ranking 294th earlier), then p_h will be greater than p_a. The fact that runner *i* was actually observed to have participated in race 28 places an upper bound on the value of $\varepsilon_{i8} - \varepsilon_{i28}$ ("UB_i") that corresponds to the value at which the runner is indifferent between race 8 and race 28 at the actual prizes. (Recall that, as explained in Section 3.3, ε_{ik} represents the idiosyncratic attractiveness of race *k* to runner *i*.) At the hypothetical prizes there is a revised critical value of $\varepsilon_{i8} - \varepsilon_{i28}$ ("CV_i") at which the runner is indifferent between race 8 and race 28. Assuming the runner is ranked better than 294th, CV_i is less than UB_i. In this case, the probability that the runner would choose race 8 at the hypothetical prizes while he chose race 28 at the actual prizes is equal to the probability that the true value of $\varepsilon_{i8} - \varepsilon_{i28}$ is between CV_i and UB_i conditional on $\varepsilon_{i8} - \varepsilon_{i28}$ not exceeding UB_i. This is equal to $\frac{p_h - p_a}{1 - p_a}$ since p_a is the probability $\varepsilon_{i8} - \varepsilon_{i28}$ exceeds UB_i and p_h is the probability it exceeds CV_i. If the runner is ranked worse than 294th, race 8 is made less attractive to runner *i* by the increase in prizes. Under these circumstances a runner who chose race 28 at the actual prizes would never switch to race 8 at the hypothetical prizes and, since $p_h < p_a$, $\frac{p_h - p_a}{1 - p_a}$ is negative. Thus, the probability of a runner participating in race 8 at the hypothetical prizes conditional on the fact that at the actual prizes he chose to participate in race 28 is the larger of $\frac{p_h - p_a}{1 - p_a}$ and zero. The first table in Appendix B.5 shows these defection probabilities for each of the 18 top runners that participated in race 28.

In a similar way for the five top runners that actually participated in race 8 we can calculate the unconditional probability of each runner choosing race 8 at the actual and hypothetical prizes. For runner *j* these probabilities are represented by $\widetilde{p}_a$ and $\widetilde{p}_h$ respectively. The fact that runner *j* was actually observed to have participated in race 8 places a lower bound on the value of $\varepsilon_{j8} - \varepsilon_{j28}$ ("LB_j") that corresponds to the value at which the runner is indifferent between race 8 and race 28 at the actual prizes. At the hypothetical prizes there is a revised critical value of $\varepsilon_{j8} - \varepsilon_{j28}$ ("CV_j") at which the runner is indifferent between race 8 and race 28. Assuming the runner is ranked worse than 294th, CV_j is greater than LB_j. In this case, the probability that the runner would choose race 8 at the actual and hypothetical prizes is equal to the probability that the true value of $\varepsilon_{j8} - \varepsilon_{j28}$ is greater than CV_j conditioned on $\varepsilon_{j8} - \varepsilon_{j28}$ being greater than LB_j. This is equal to $\frac{\tilde{p}_h}{\tilde{p}_a}$. If the runner is ranked better than 294th, race 8 is made more attractive to runner j by the increase in prizes. Under these circumstances a runner who chose race 8 at the actual prizes would always choose race 8 at the hypothetical prizes and, since $\tilde{p}_h > \tilde{p}_a$, $\frac{\tilde{p}_h}{\tilde{p}_a}$ is greater than one. Thus, the probability of a runner participating in race 8 at the hypothetical prizes conditional on the fact that at the actual prizes he also chose race 8 is the smaller of $\frac{\tilde{p}_h}{\tilde{p}_a}$ and one. The second table in Appendix B.5 shows these probabilities.

In the case of the top runners originally in race 28, for eight runners the probability of defecting to race 8 exceeds 10%, for three runners the probability is between zero and 5% and for the remaining seven runners the probability is zero. In order to simplify the analysis only those runners with a 10% or greater chance of defection will be considered in the remainder of the discussion. In the case of the five runners originally in race 8, based on the hypothetical prizes three are estimated to remain in race 8 with certainty while two are estimated to defect to race 28 with a probability of less than 5%. For simplicity the possibility of defections away from race 8 will be ignored in the remainder of the analysis. Based on these simplifying assumptions the probability of at least one runner from race 28 joining race 8 if the hypothetical prizes were introduced is 0.7 and the expected number of runners defecting from race 28 to race 8 is 1.2. This is the sorting effect in action.

Now we turn to the incentive effect of the hypothetical revised prizes on the runners already committed to race 8. We call the predicted effect of the revised prizes before taking into account the impact of runners defecting into race 8 the “direct” incentive effect. We call the total effect of the hypothetical prizes when allowing for defections the “combined” incentive effect and the difference between these two effects the “indirect” incentive effect. As shown in the third table in Appendix B.5, we estimate the combined incentive effect to be of the order of 0.5% of the runners’ original times. Except in the case of the top ranked runner in race 8 the direct incentive effect represents the overwhelming majority of this predicted change in speed. For the top ranked runner in race 8 the indirect incentive effect is larger than is the case for the other runner since for this runner three of the runners that may defect from race 28 are within 20 ranking places and therefore the local competitive effect has a positive impact on the runner’s predicted speed.

As we have chosen to model them, the direct incentive effect is common to all race participants while the indirect incentive effect can vary between individuals since the hypothetical change in prizes can result in changes in local competitive intensity that differs between runners of different rankings. In the particular example that has been worked out here the direct incentive effect is larger the indirect incentive effect. Of course, this may not be true for other races and other runners.

3.7 Conclusions

Tournaments of many types are important in the economy. In many cases data are difficult to collect and, as a result, to a large extent empirical analysis has not been available to support the development of theory. If it can be shown that participants respond to the observed financial prizes, sports tournaments may offer a fruitful area for study that complements research in areas of more direct interest but where data may be limited and of poor quality. In a sense sports tournaments provide an analytical bridge between laboratory experiments and economically important tournaments. In the case of laboratory experiments data are of high quality but the applicability to other economically important tournaments may be questioned. In the case of a direct study of say work place promotions, the applicability is clear while high quality data may be scarce. Sports tournaments stand between these two extremes and may play an important part in furthering understanding.

This chapter's contribution is fivefold. First, we elaborate a two-part model to separately quantify the sorting and incentive effects of tournament prizes. We believe that in this setting our approach is novel. Second we apply the model to a unique data set of road running race results. Since, unlike the data sets used in prior studies we are aware of, the one used here includes runners that did not win prizes, it allows us to observe the impact of prizes on the race choice and the speed of all runners, not just prize winners. Third, we use concepts of global and local competitiveness to estimate effects that relate to the overall competitiveness of a race and the local impact of runners of similar rank to the runner of interest. Fourth, we demonstrate that in the races we examine participants do indeed respond to financial prizes and both sorting and incentive effects are present. These conclusions are robust to a number of alternative specifications of the sorting and speed equations. Fifth, we present a counterfactual example showing how a hypothetical change in prizes would be predicted to change race participation and speed.

CHAPTER 4

THE PRICE IMPACT OF RETAILERS' LOCATIONS AND BRANDS[11]

4.1 Introduction

To suggest that the physical locations and the brands of retailers are important in consumer markets is unremarkable. As consumers we know that, all other things being equal, a conveniently located retailer of our preferred brand will be more attractive to us than one that is less easy to reach or is of a less appealing brand. However, depending as it does on the aggregate behavior of consumers and retailers, the combined effect of location and brand on market prices is complex. In this chapter we present a new approach to measuring the impact of retailers' locations and brands on market prices. Unlike prior researchers, we flexibly model the impact of competing retailers and rather than limiting our analysis to predetermined nearby locations we allow for the possibility that more distant retailers have an impact.

We apply our novel approach to data from the retail gasoline market in Tucson, Arizona. We show that in the Tucson gasoline market, increased brand diversity is associated with higher prices. As we discuss in Section 4.3, this is consistent with the price effect from consumers having preferences over brands being larger in magnitude than the price effect from retail outlets sharing the same brand coordinating prices. We also demonstrate that

[11] This chapter is co-authored with Jedidiah Brewer and Joseph Cullen.

on average, gas stations affiliated with mass-merchandisers and grocery stores have a larger impact on prices over a greater distance than other types of gas stations. This suggests that the low-price strategy followed by these gas stations and the attractiveness of their affiliated stores intensifies price competition locally, leading to lower equilibrium prices over a wider area than is the case for other gas stations. We use road distances, Euclidean distances and travel times to measure the distances between gas stations in our analysis. We show that our findings are not sensitive to the choice of distance metric.

4.2 Relevant Literature

Two relevant areas of research are discussed below: (1) empirical studies of retail gasoline markets; and, (2) a study that investigates the use of alternative measures of distance.

4.2.1 The Retail Gasoline Market

There is a fairly extensive literature that considers industry structure and pricing in the retail gasoline market. In contrast to the analysis described later in this chapter, in general researchers have used predetermined market areas based on Euclidean distances to evaluate the degree of competition faced by a retail outlet.

Shepard (1991) uses gas station data to investigate competition between multi-product and single-product providers. The analysis uses the average price for competitors located within a specified Euclidean distance (half, one, one and a half or two miles) from the gas station of interest as an explanatory variable. Pinkse and Slade (1998) investigate gas station supply contract choices. The authors compare six metrics of competitive closeness (Euclidean distance, location on same street, a combination of the first two methods, nearest neighbor on street, nearest neighbor, and common boundary) and conclude that nearest neighbor is the most appropriate measure. Barron, Taylor and Umbeck (2000) investigate the relative pricing of regular and premium gasoline. The authors use the Euclidean distance to the nearest competitor as an explanatory variable. Netz and Taylor (2002) investigate how gas stations locate as competition increases. Competition is measured based on the number of stations within either half, one or two Euclidean miles of the gas station of interest. Barron, Taylor and Umbeck (2004a) investigate the impact of different contractual supply arrangements on retail gasoline prices. In the analysis the number of competitors within a specified Euclidean distance from the gas station of interest and the Euclidean distance to the nearest competitor are used as explanatory variables. Barron, Taylor, and Umbeck (2004b) examine the impact of the density of competitors on prices. The authors measure competitor density by counting the number of stations within one and a half Euclidean miles of the station of interest and find that as density increases, posted prices fall. Barron, Umbeck, and Waddell (2006) conduct a field experiment and demonstrate that competitor density impacts a station’s price elasticity of demand and the responses of competitors to an exogenous change in another station’s price. The authors measure competitor density by counting the number of stations within two Euclidean miles of a given station.

An exception to the pattern of relying on Euclidean distance measures is Hastings (2004) in which the number of competitors in market areas based on road distances are used to measure the level of competition a retail location experiences.

4.2.2 Alternative Distance Metrics

In general, economists have not considered the importance of different distance measures in spatial analysis. This approach has been defensible in the past since in many applications spatial effects were of secondary importance only, and alternatives to Euclidean distances were prohibitively costly to collect. Given the improvement in the cost and ease of use of geographical information system ("GIS") software and the greater availability of location coded data sets the usual approach may no longer be appropriate. Apparicio et al (2003) discuss the relative advantages and disadvantages of four measures of distance: Euclidean distance; Manhattan distance; shortest road distance; and, shortest road travel time. Euclidean distance is the straight line distance between two points. Manhattan distance is the distance along two sides of a right angle triangle, where one of the sides measured runs North/South and the other runs East/West and with the hypotenuse corresponding to the Euclidean distance. Shortest road distance takes into account the actual location of roads to estimate the shortest route between two points. Shortest road travel time takes into account road locations and estimates of actual travel speeds to estimate the time to travel between two points. Apparicio et al (2003) compare these four distance measures in eight Canadian metropolitan areas and find that the measures are all closely correlated across the eight metro areas but that within each metro area the measures can vary substantially. The authors conclude that "for the study of general metropolitan phenomena Euclidean and Manhattan approximations are adequate, but as soon as specific sub-metropolitan areas or neighborhoods are considered there are substantial benefits to using network based distances and times."

4.3 Background and Theory Discussion

When evaluating a gas station's physical location we take into account both its location before taking into account the location of other gas stations (we term this "absolute spatial location") and its position relative to other gas stations (we term this "relative spatial location"). In the case of brands, we use the term "absolute brand location" to refer to a gas station's brand without considering the brands of other outlets and the term "relative brand location" to refer to a metric that takes into account the brands of other outlets that are present in the marketplace.

We would anticipate a retailer's absolute spatial location to be important since, for example, demand may vary geographically leading to higher prices in areas of unusually high demand and lower prices in areas of low demand. With regard to relative spatial location, all other things being equal, we would expect a lower density of nearby gas stations to be associated with higher prices. This is the case since a lower density of competitors means that consumers benefit from fewer close substitutes which in turn reduces the price elasticity of demand for individual outlets and, assuming each outlet behaves as an independent profit maximizer, increases equilibrium prices.

In the case of brands, we would expect absolute brand location to be important since certain brands may, for example, be associated with a particularly high or low quality of service (reflecting consumers' preferences for particular gasoline additives or the stations' state of cleanliness and the like) resulting in higher or lower than average prices. With respect to relative brand location, we investigate the relationship between market prices and the degree of brand diversity that is present locally. Theoretically in this context brand diversity's impact on prices is ambiguous. If consumers have preferences over brands, increased brand diversity may reduce the density of close substitutes, leading to increased equilibrium prices (we call this the "brand loyalty" effect). However, if retail outlets of the same brand follow a coordinated pricing strategy then increased brand diversity may result in more intense competition and lower equilibrium prices (we call this the "brand competition" effect). The net result from these two offsetting effects is theoretically unclear and is a matter for empirical investigation.

As a result of the range of prevailing ownership and contractual arrangements in the retail gasoline industry, the degree to which gas stations of the same brand would be expected to coordinate pricing is uncertain. The ownership of branded gas stations falls into three basic types. The first type is a company-owned-and-operated station. The refiner owns the station and an employee of the refiner runs the station. In this case retail prices are set by the refiner. The second type is a lessee-dealer. The refiner owns the station and leases it to an operator. In this case the lessee is responsible for setting retail prices. The third type is a dealer-owned station. In this case the operator owns the station and is responsible for setting retail prices.[12] Due to these alternative ownership and operating arrangements two gas stations that bear the same brand (e.g., Chevron) may or may not be commonly owned and even if they are commonly owned, due to the possible presence of lease agreements, they may or may not have their prices set by the same individual or organization.

It should be noted that absolute spatial location can be determined without considering brands, and in a similar fashion absolute brand location does not involve defining geographical locations. This is not true of relative spatial and relative brand locations. In both of these cases it is necessary to define the size of the market in terms of geography and brands. So, for example, in order to determine the density of gas stations surrounding the station of interest it is necessary to specify the range of brands and the geographic scope that characterize the market. The same is true in assigning a value to brand diversity.

In the retail gasoline market, we believe that the extent of the market with respect to brands is relatively clear: we include all retailers that sell gasoline to the public in our analysis. As far as geographic market size is concerned, we regard the situation as more ambiguous. Certainly, the degree of direct competition between two stations 100 miles apart is negligible and they should not be considered to be in the same market, whereas competition between stations located across the street from one another is strong, clearly placing them in the same market. But what about stations that are two, three, four or five

[12] Hastings (2004) includes a more detailed discussion of ownership arrangements in the retail gasoline industry.

miles apart? How should they be treated? A priori we have no compelling way to answer this question. For this reason we chose to determine the geographic scope of the market for each outlet flexibly. We avoid imposing a predetermined geographical market and instead estimate the geographic extent of competition based on the data. We also allow the degree to which two outlets should be considered to be in the same market to diminish smoothly with distance rather than imposing sharp boundaries. In keeping with our goal of defining geographical market areas flexibly, we investigate three alternative metrics for measuring the distance between gas station locations: road distance; Euclidean distance; and, travel time.

Our flexible approach to geographic market areas is particularly appropriate for examining whether different categories of retailers have different market impacts. We use this feature to compare hypermarts to other types of gas stations. Hypermart is an industry term used to describe non-traditional retail gasoline locations. Typically traditional gas stations are located on major streets and intersections. Common examples of traditional gas stations are Chevron, Shell, and Texaco. Hypermarts, on the other hand, are mass-merchandisers and grocery stores that have entered the retail gasoline industry primarily over the last decade. Examples include Costco, Safeway, and Wal-Mart. Hypermarts characteristically locate in the larger stores' parking lots, price low, sell high volumes of gas, and offer few of the amenities such as convenience stores, car washes, and repair shops often offered by traditional gasoline retailers. From time to time, industry participants have expressed the view that hypermarts depress market prices.[13] Our modeling approach makes it possible to investigate whether or not this is in fact the case.

Although absolute spatial location and absolute brand location have routinely been considered by researchers, the same can not be said of relative spatial location and relative brand location. Relative spatial location effects have received only limited attention from economists. If they have been modeled, ease of data collection has tended to override other considerations. As a result, measures such as the shortest distance to a competitor, or the number of competitors located less than some critical distance from the outlet of interest have been employed. As far as we are aware, relative brand location effects of the type we have discussed in this section have not previously been studied empirically and we are the first to examine the relative magnitudes of the brand loyalty and brand competition effects. We believe that the flexible approach we use to define the geographic scope of the relevant market areas is new. In addition, although researchers elsewhere in the social sciences have considered the issue, we are not aware of economists systemically investigating the consequences of using alternative distance metrics.

4.4 Description of the Data

Our data set includes posted prices, characteristics and locations for 235 retail gasoline

[13] An illustrative example is provided by an article in the Denver Business Journal on April 2, 2001 entitled "Hypermarts siphon independents' gas sales." In part the article states that "Cliff Brice Stations Inc. sold gasoline to Pueblo drivers for three generations and was the largest independent gas station company in town. But the company only lasted three years after hypermarts – combination retail or grocery stores with gas stations in the parking lots – started opening in Pueblo. Brice said his stores couldn't compete with the new combination gas stations that sold gasoline cheaper, from 10 cents to 12 cents per gallon cheaper, than his own stations."

outlets in Tucson, Arizona. The data were collected over a 14-hour period on March 12, 2005.[14] We believe we have included all gas stations in the metropolitan area of Tucson in service at the time the data were collected. Table 4.1 shows price observations by brand and retailer type.

Table 4.1

Regular Gasoline Pricing Statistics by Brand or Type of Station

Brand/type	Average price	Standard deviation	Minimum price	Maximum price	Observations
Arco	$1.969	$0.011	$1.95	$1.99	11
Diamond Shamrock	1.971	0.005	1.97	1.99	14
Hypermart	1.972	0.019	1.95	1.99	8
Conoco	1.983	0.028	1.96	2.05	11
Quik-Mart	1.986	0.008	1.97	1.99	14
Circle K	1.993	0.024	1.94	2.07	83
Other	1.998	0.039	1.95	2.13	19
Citgo	2.030	0.000	2.03	2.03	6
76	2.030	0.031	1.99	2.07	7
Exxon	2.043	0.028	1.99	2.08	8
Mobil	2.043	0.013	2.03	2.07	13
Shell	2.060	0.030	2.01	2.11	10
Texaco	2.060	0.020	2.04	2.09	5
Chevron	2.074	0.050	1.99	2.29	26

A total of ten types of branded gas stations were observed accounting for a total of 111 stations. Consistent with the literature, only those stations branded with the name of an oil refiner were considered to be branded stations. Eight stations were categorized as hypermarts and 116 as unbranded. Unbranded stations included 83 Circle K stations, 14

[14] The data were collected by Jedidiah and Jordan Brewer.

Quik-Mart stations and 19 stations of miscellaneous other types.[15] The lowest price observed for one gallon of regular gasoline was $1.94 and the highest $2.29.

In addition to a gas station's location, prices, and brand, the presence of a convenience store, franchise food restaurant, car wash or repair shop are recorded in the data set. For the 235 locations a total of 209 convenience stores, 18 franchise food restaurants, 14 car washes, and 19 repair shops were observed.

Table 4.2

Population Density and Traffic Flow Summary Statistics

	Mean	Standard deviation	Minimum	Maximum	Observations
Population density	2,610	1,771	19	5,384	235
Traffic flow	46.52	24.43	3.10	107.25	235

Two additional variables were included in our model to control for demand effects: population density and traffic flow. The summary statistics for these variables are shown in Table 4.2. As far as we are aware, traffic flow, which appears to us to be a strong candidate to proxy demand in the retail gasoline market, has not been used as a control variable by prior researchers. Population density is measured in units of individuals per square mile and traffic flow in terms of thousands of vehicles per day. Population density was measured by zip code based on data from the US Census Bureau. Traffic flow data were obtained from the Pima County Department of Transportation. If a station was located at an intersection, then the station was credited with the sum of the traffic flows on both intersecting streets. We experimented with including census data for median

[15] Stations that are branded with the name of a non-refiner such as Circle K or Quik-Mart are sometimes said to be "private-branded."

income by zip code as an additional control variable. Since we found the coefficient for this variable not to be statistically significantly different from zero, it was not included in the analyses shown in this chapter.

4.5 Econometric Model

Our econometric model for gas prices is shown in Equation 4.1.

$$\begin{aligned} p_i = X_i\beta + (\text{hypermart count}_i)\lambda_h + (\text{non}-\text{hypermart count}_i)\lambda_n \\ +Log(\text{Herfindahl Index of brand counts}_i)\mu + \varepsilon_i \end{aligned} \quad (4.1)$$

In Equation 4.1 p_i represents the posted price for a gallon of regular gas at station i. X_i is a vector of exogenous station characteristics consisting of location-specific characteristics (population density and traffic flow) and dummy variables for station characteristics (brand, convenience store, franchise food outlet, car wash and repair shop). The hypermart and non-hypermart counts are our measures of the density of surrounding gas stations. The Herfindahl index of brand counts serves as our measure of brand diversity. The final term, ε_i, is an i.i.d. disturbance term. The manner in which the hypermart and non-hypermart counts and the Herfindahl index of brand counts were calculated is explained below.

In counting the gas stations surrounding the station of interest i, each station j is assigned a weighting factor w_{ij} that declines with distance from station i as shown in Equation 4.2.

$$w_{ij} = \frac{\phi\left(\dfrac{d_{ij}}{\alpha}\right)}{\phi(0)} \quad (4.2)$$

In Equation 4.2 $\phi(.)$ is the probability density function for a standard normal distribution, d_{ij} is the distance from the station of interest i to station j and α is a distance normalization factor that will be estimated.[16] Given our specification of w_{ij}, if $d_{ij} = 0$ then w_{ij} is equal to one and as d_{ij} increases w_{ij} declines smoothly towards zero. For example, if $d_{ij} = \alpha$ then w_{ij} is equal to 0.61 and if $d_{ij} = 2\alpha$ then w_{ij} is equal to 0.14. In order to investigate whether hypermarts have a different impact on prevailing prices than other types of gas stations, different values of the distance normalization factor were allowed for hypermarts and non-hypermarts. (We designate these values α_h and α_n for hypermarts and non-hypermarts respectively.) The manner in which the counts for hypermart and non-hypermart gas stations were calculated for station i are shown in Equation 4.3.

$$\text{hypermart count}_i = \sum_{\substack{\text{all } j \text{ where } j \text{ is} \\ \text{a hypermart} \\ \text{and } j \neq i}} w_{ij} \,, \quad \text{non-hypermart count}_i = \sum_{\substack{\text{all } j \text{ where } j \text{ is} \\ \text{not a hypermart} \\ \text{and } j \neq i}} w_{ij} \qquad (4.3)$$

As is clear from Equation 4.3, our hypermart and non-hypermart counts are sums of the applicable weighting factors and as such they reflect the number of stations of the specified type in the data set and the distance separating the stations from the station of interest. Since the weighting factors vary depending upon the distances between the station of interest and all surrounding stations with greater weight being given to nearby

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[16] An equivalent formulation for Equation 4.2 is $w_{ij} = e^{-\frac{1}{2}\left(\frac{d_{ij}}{\alpha}\right)^2}$.

stations, in general the hypermart and non-hypermart counts will be different for each station.

We believe that the use of a factor based on the normal probability density function to weight the count of surrounding gas stations as shown in Equation 4.2 is appropriate since: (1) it avoids imposing a predetermined market size; (2) it allows all stations in the market to have an impact; (3) its form corresponds to the intuition that nearby stations have significant impact while distant ones do not; and, (4) its smooth character and parsimonious coefficient requirements facilitate estimation. For these reasons we prefer it to the traditional "number of stations within *y* miles" approach. In addition, since many individuals are likely to purchase gas while making journeys that are primarily for other purposes, if consumers choose from among stations close to their planned route, we would like the weighting factors to correspond to the probability that given an individual will be passing close to station *i*, she will also be passing close to station *j*. The general form of the normal probability density function seems plausible under these circumstances. Normalizing the weighting factors by $\phi(0)$ is consistent with the probability explanation. It also simplifies the interpretation of the coefficients of the counts for hypermarts and non-hypermarts, λ_h and λ_n, since it means that they correspond to the expected price impact of an additional hypermart or non-hypermart located arbitrarily close to the gas station of interest.

Presumably the "correct" weighting factors that reflect the true extent to which consumers consider different stations to compete with each other depend on consumers' journey patterns and the search methods they use for determining their preferred stations. We are not in a position to estimate these directly but as we have argued here we believe that the weighting factors we use as shown in Equation 4.2 are plausible approximations.

In order to calculate the Herfindahl index of brand counts, similar distance weighted counts to those indicated in Equation 4.3 were undertaken for each brand present in the market. For these purposes, unbranded stations were treated as a single category and all hypermarts were considered as a single category. The count corresponding to the brand of the station of interest was adjusted to include the station of interest.

We define the brand share of brand *x* for station *i* as being equal to the count for brand *x* for station *i* divided by the sum of similar counts for all the brands present in the marketplace. Therefore, if $share_{ix}$ is the brand share of brand *x* for station *i* and *Z* is the set of all the brands in the marketplace, $share_{ix}$ is calculated as shown in Equation 4.4.

$$share_{ix} = \frac{x \text{ count}_i}{\sum_{\text{all } z \in Z} z \text{ count}_i} \qquad (4.4)$$

The Herfindahl index of brand counts for station *i* was then calculated in the usual way as shown in Equation 4.5.

$$\text{Herdindahl index of brand counts}_i = \sum_{\text{all } x \in Z} \left(share_{ix}\right)^2 \qquad (4.5)$$

A value of one for the Herfindahl index of brand counts would correspond to no brand diversity at station i and a value close to zero would correspond to very high brand diversity. As described above, we calculate brand shares using counts that are determined by summing weighting factors based on distances from the station of interest. Thus, our Herfindahl index of brand counts is similar in character to more conventional measures of market concentration that use market shares based on sales. As is the case with the hypermart and non-hypermart counts, in general the value of the Herfindahl index of brand counts will be different for each station. Note that in calculating the Herfindahl index of brand counts the station of interest i is included in the analysis and gets the highest count weight. Therefore this variable reflects both the variability in brands of the surrounding stations (with greater weight given to those stations that are close by) and the difference in brand between the surrounding stations and the station of interest.

We believe that the data we use for our analysis displays sufficient variability in order to identify all the parameters in our model. In particular, λ_h and α_h and λ_n and α_n are separately identified since there is variety in both the absolute number of the relevant type of stations at specified distances from the various station locations and variety in the relative number of stations at each distance. Similar variability in the locations of the various brands present in the marketplace identifies μ.

In Section 4.7 when we report our results we will assume that the coefficients we estimate based on our model can be interpreted causally. We believe this to be reasonable because: (1) we consider it to be improbable that marginal costs and other factors that could influence supply vary systematically across stations in a way that is not reflected by the brand dummies; (2) we believe that we are appropriately controlling for demand; and, (3) observed station characteristics other than price can not be changed at short notice and therefore we believe that these can reasonably be considered as exogenous in the price setting decision.

Consistent with the findings of prior researchers, we would expect market prices to increase as the density of surrounding outlets decreases and therefore we would expect λ_h and λ_n to be negative. If the views of industry participants are correct, we would anticipate our results to indicate that hypermarts have a greater negative impact on prices than other types of gas stations. As discussed earlier, theoretically the impact of a change in brand diversity is ambiguous and therefore we do not have any prior expectations regarding the sign of μ.

In order to investigate the robustness of our findings based on estimating the model described in this section, we also considered a number of alternative models that change the treatment of unbranded stations, vary the form of the weighting factors, account for possible residual spatial autocorrelation and examine the impact of common ownership of stations. These alternative models and the results we obtained from using them are described in Section 4.8.

4.6 Distance Measurement Methodologies

In order to investigate how sensitive our results are to the distance measure chosen and to explore the issues raised in Apparicio et al (2003), we estimated the model using three distance measures: Euclidean distance; road distance; and, travel time.

Since we wished to allow for the possibility of all gas stations influencing prices at all other stations it was necessary to calculate the distances between all station locations and all other station locations. The first step in obtaining the distance matrices was to place the gas station locations in geographic space in a GIS. This required a reliable road network containing all roads in the greater Tucson area to use as our base for geocoding. We obtained the road GIS data from the Pima County Department of Transportation. We used local data rather than national level census road data because the census GIS is not updated regularly to reflect the changing road network. Setting up a GIS and geocoding locations can be time consuming. Differences in road names and abbreviations can require changes to the road GIS and in some cases requires the hand plotting of locations. In addition, even with the more accurate local data we had to correct some obvious addressing errors resulting from errors in the underlying road network. Once the gas stations were placed in geographic space, calculating the Euclidean distances was trivial. It took only a few seconds to calculate over 50,000 distance measurements. Finding road distances using a GIS is a more complicated process. In order to determine the routing necessary for road distance measurements, a geometric network must be created from the road GIS data. If there are errors in the GIS data, either in road attributes or geometric errors in road intersections, an erroneous geometric network is created. Even small errors in the network can cause significant measurement error in road distance. The local road data compiled by the transportation authority had not been created for the purpose of routing. Given that we had already found some small mistakes in the data, the road GIS would need to be checked for accuracy, a labor-intensive and time consuming process. Given our concerns about the applicability of our GIS for routing, we decided to use MapQuest.com, an Internet GIS specifically designed for routing, to obtain our road distance and travel time measurements. The advantages of using a service such as MapQuest are: (1) the routing is based on proprietary data that generally reflects the most accurate data available; and, (2) the complex task of routing is handled using efficient algorithms. The disadvantages are: (1) distance acquisition is relatively slow since each distance must be queried via the Internet[17]; and, (2) the routing algorithm is a black box; we do not known how road distances or travel times are derived. We do know that the measurements of distance and time are not independent. The routing algorithm does not search for the shortest distance between two points and then search for the shortest travel time between the same two points; rather, the algorithm chooses the "best" route between two points and returns the corresponding distance and travel time.

The methods we used to obtain distances resulted in road and Euclidean distances measured in miles to the nearest foot and travel times measured in whole minutes, with no times less than one minute.

4.7 Results from the Empirical Analysis

Since the hypermart count, the non-hypermart count and the Herfindahl index of brand counts contain non-linear transformations of the observed data, we used non-linear least

[17] Since we had 235 observations, we needed to fill out a 235x235 matrix of distances. This required 235x(235 – 1) = 54,990 distances to be calculated. (The diagonal elements do not have to be calculated because they are always equal to zero.) It took approximately 24 hours for our computer program to extract all the required road distances and travel times from the Internet.

squares to estimate the model described in Section 4.5. Table 4.3 summarizes the results from estimating the model using road distances as the measure of distance. Appendix C.1 includes equivalent results using Euclidean distances and travel times.

Table 4.3

Results Using Road Distances

	Coefficient value	s.e.	p value	90% confidence interval low	high
Constant	1.994***	0.009	0.000	1.979	2.009
Population density	2.819E-06*	1.490E-06	0.058	3.690E-07	5.269E-06
Traffic flow	0.000154*	0.000090	0.087	0.000006	0.000302
Hypermart	-0.030**	0.012	0.014	-0.050	-0.010
Arco	-0.028***	0.009	0.001	-0.043	-0.014
Chevron	0.071***	0.007	0.000	0.060	0.083
Conoco	-0.011	0.009	0.198	-0.025	0.003
Citgo	0.035***	0.011	0.002	0.016	0.053
Diamond Shamrock	-0.025***	0.008	0.001	-0.037	-0.012
Exxon	0.044***	0.010	0.000	0.027	0.061
Mobil	0.041***	0.008	0.000	0.028	0.055
Shell	0.060***	0.009	0.000	0.045	0.076
76	0.020*	0.012	0.079	0.001	0.040
Texaco	0.060***	0.013	0.000	0.039	0.082
Convenience store	-0.007	0.008	0.376	-0.019	0.006
Franchise food outlet	0.013*	0.007	0.061	0.002	0.025
Car wash	0.004	0.009	0.650	-0.010	0.018
Repair shop	0.014*	0.007	0.053	0.002	0.026
α hypermarts (α_h)	1.458**	0.656	0.026	0.380	2.537
λ hypermarts (λ_h)	-0.014**	0.007	0.050	-0.025	-0.002
α non-hypermarts (α_n)	0.872***	0.208	0.000	0.530	1.215
λ non-hypermarts (λ_n)	-0.005**	0.002	0.046	-0.009	-0.001
Log of HI of brand counts (μ)	-0.024*	0.013	0.073	-0.045	-0.002

"*", "**" and "***" indicate statistical significance at the 10%, 5% and 1% level respectively.

As expected, the results in Table 4.3 show that prices increase with population density and traffic flow which are anticipated to be associated with increased gasoline demand. Both of these coefficients are statistically significant at the 10% level. The coefficients for the dummy variables for gas station type and brand are in general statistically significant and are of plausible signs and magnitudes with premium brands like Chevron having a positive sign and Hypermarts having a negative sign. Note that these dummy variables indicate the difference between prices at the relevant type of station and the baseline group of unbranded stations. In terms of amenities located at the gas station, franchise food outlets and repair shops are associated with prices that are higher by 1.3¢ and 1.4¢ respectively. Both of these coefficients are statistically significant at the 10% level. In contrast, the presence of convenience stores and carwashes are not associated with any statistically significant price difference.

The coefficients for hypermart and non-hypermart counts, λ_h and λ_n, and the corresponding distance normalization factors, α_h and α_n, are all statistically significant at the 5% level. As expected, λ_h and λ_n are both negative, and α_h and α_n are both positive, indicating that an increase in the number of competing stations or a reduction in their distance from the station of interest results in a fall in posted price. λ_h is greater in absolute value than λ_n and α_h is greater than α_n indicating that a hypermart has a larger negative impact on prices and influences prices over a greater distance than a representative non-hypermart gas station.[18] Based on a likelihood ratio test, the null hypothesis that $\lambda_h = \lambda_n$ and $\alpha_h = \alpha_n$ can be rejected with a p value of 0.16. Thus, although our results are suggestive, they provide only weak statistical evidence for the hypothesis that $\lambda_h < \lambda_n$ and $\alpha_h > \alpha_n$. Using the estimated parameters and the corresponding variance/covariance matrix, and applying the delta method, the null

[18] This result is consistent with the findings of Brewer (2006).

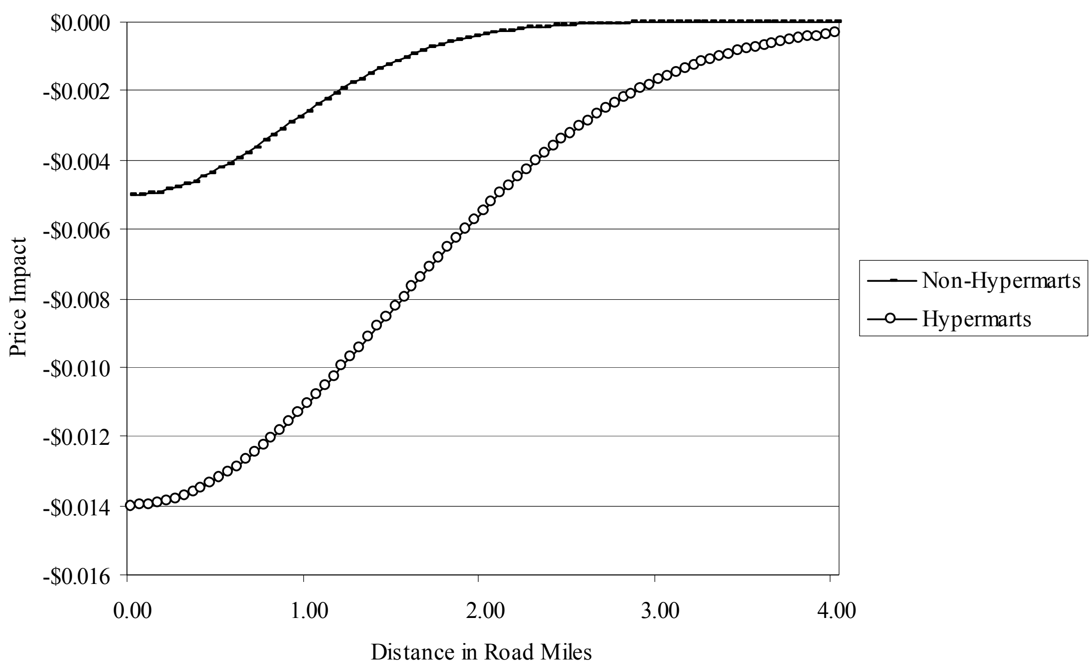
hypothesis that a hypermart has less of a price impact at a distance of one mile than an equivalently located non-hypermart can be rejected with a p value of 0.09. Thus, our results offer reasonably persuasive evidence that hypermarts do in fact have a stronger impact on prices than non-hypermarts.

As discussed in Section 4.5, in light of the variables included in the model to control for demand and given the fact that marginal costs and other factors relating to supply are unlikely to vary systematically between stations, we believe it is improbable that omitted variables are biasing our findings. If we are wrong on this point, we are of the view that the most plausible situation would be that our control variables fail to fully account for the higher demand associated with hypermart locations. If this is in fact the case, all other things being equal, prices at hypermart locations would be higher than our model would otherwise predict and as a consequence our reported value of λ_h would be biased upwards towards zero. Therefore if bias is present it is likely that our reported results understate the difference between hypermarts and non-hypermarts and our conclusion that on average hypermarts have a larger negative impact on prices than non-hypermarts would still hold.

Using the results shown in Table 4.3, Figure 4.1 plots $\frac{\phi\left(\frac{d_{ij}}{\alpha_h}\right)}{\phi(0)}\lambda_h$ and $\frac{\phi\left(\frac{d_{ij}}{\alpha_n}\right)}{\phi(0)}\lambda_n$ for values of d_{ij} from zero to four miles in order to illustrate how the implied price impact of an additional hypermart or non-hypermart varies with distance from the station of interest. Appendix C.1 includes equivalent figures based on the results using Euclidean distances and travel times.

Figure 4.1

Estimated Price Impact of Hypermart and Non-Hypermart Gas Stations Based on Road Distance from Station of Interest



As shown in Table 4.3, the coefficient for the log of the Herfindahl index of brand counts, μ, is negative and statistically significant at the 10% level. The sign of the coefficient indicates that higher brand diversity is associated with higher prices, and vice versa. This result suggests that the price impact resulting from brand loyalty more than offsets the effects of brand competition. For example, consider two otherwise identical gas stations where the first is in a market with no brand diversity (and therefore the Herfindahl index of brand counts is equal to one) and the second has significant brand diversity such that the Herfindahl index of brand counts is 0.1. The station with the higher local brand diversity would have a 2.4¢ higher price.[19]

Table 4.4 shows the estimated values of λ_h, α_h, λ_n, α_n and μ for each of our three measures of distance (road distances, Euclidean distances and travel times). Note that in all cases $\lambda_h < \lambda_n < 0$, $\alpha_h > \alpha_n > 0$ and $\mu < 0$ and therefore the qualitative conclusions we have drawn do not depend upon the choice of distance metric used. Since λ_h and λ_n can be interpreted as estimating the price impact in dollars of an additional hypermart or non-hypermart respectively located arbitrarily close to the gas station of interest, a direct comparison of their numerical values is meaningful. As can be observed, the values are not materially changed by the choice of distance metric.

Table 4.4

Comparison of Results Based on Alternative Distance Metrics

	Distance metric used		
	Road distances	Euclidean distances	Travel times
λ hypermarts (λ_h)	-0.0137 (0.0070)	-0.0126 (0.0060)	-0.0120 (0.0080)
α hypermarts (α_h)	1.4584 (0.6558)	1.0633 0.4756	2.6537 (1.5230)
λ non-hypermarts (λ_n)	-0.0048 (0.0024)	-0.0051 (0.0027)	-0.0038 (0.0024)
α non-hypermarts (α_n)	0.8724 (0.2081)	0.6977 (0.1717)	2.0906 (0.5702)
Log of HI of brand counts (μ)	-0.0237 (0.0132)	-0.0210 (0.0139)	-0.0272 (0.0138)

Standard errors are indicated in parentheses.

[19] At the estimated values of α_h and α_n, the observed average value of the Herfindahl Index of brand counts was 0.39, the maximum value was 1.00, the minimum value was 0.17 and its standard deviation was 0.20.

4.8 Robustness Checks

In order to check the robustness of our results, we estimated a number of variations of our model designed to investigate the sensitivity of our findings to: (1) the characterization of unbranded stations; (2) the form of the weighting formula shown in Equation 4.2; and, (3) the possible presence of residual spatial autocorrelation in the disturbance term. In addition, we investigated whether common ownership of stations was important in explaining pricing.

4.8.1 Characterization of Unbranded Stations

To investigate if our findings might be influenced by the large number of unbranded stations included in the count of non-hypermart gas stations, we estimated a model which, for the purposes of calculating the non-hypermart count, separated non-hypermarts into unbranded and branded stations and utilized separate counts for these new categories. The results of the model following this approach (the "1st adapted model") are shown in Appendix C.2. Although the coefficient for the unbranded station count, λ_{ub}, and the distance normalization factor for branded stations, α_b, are not statistically different from zero at the 10% level, the results are generally consistent with those discussed earlier. Importantly for our purposes, the estimated values of the coefficients for the counts for hypermarts, unbranded stations and branded stations are all negative with λ_h being the largest in absolute value and the estimated values of the distance normalization factors are all positive with α_h being the largest. In addition, the coefficient of the log of the Herfindahl index of brand counts is negative and is statistically significantly different from zero at the 5% level.

Our second investigation of the effect of our treatment of unbranded stations was to estimate a revised version of the model which, for the purposes of calculating the Herfindahl index of brand counts, divided the unbranded category into three sub-categories: Circle K stations; Quik-Mart stations; and, Other stations. As discussed earlier, there are 83, 14 and 19 stations respectively in each of these sub-categories. The results of the model following this approach (the "2nd adapted model") are shown in Appendix C.3. The results in the first table in Appendix C.3 treat all the Other stations as a single category for the purposes of calculating the Herfindahl index of brand counts. In the case of the second table in Appendix C.3 each of the Other stations is treated as a different category when calculating the Herfindahl index of brand counts. The results are consistent with our earlier findings. In particular, in both cases $\lambda_h < \lambda_n < 0$, $\alpha_h > \alpha_n > 0$ and $\mu < 0$. All the relevant coefficients are statistically different from zero at the 10% level with the exception of λ_h in the second case which has a p value of 0.101. In addition, the coefficients for the dummy variables for Quik-Mart and Other are not statistically different from zero at the 10% level. Since Circle K stations represent the baseline, this implies that neither Quik-Mart stations nor the stations included in the Other category have prices that are statistically different from Circle K stations at the 10% level.

4.8.2 Form of Weighting Factors

As discussed earlier, we believe that the form of the weighting factors shown in Equation 4.2 is reasonable. In order to check if our findings are sensitive to this assumption, we experimented with two alternative parameterizations. Appendix C.4 shows results from using weighting factors with the forms $w_{ij} = e^{-\left(\frac{d_{ij}}{\alpha}\right)}$ and $w_{ij} = e^{-\left(\frac{d_{ij}}{\alpha}\right)^3}$. In the first case the rate of decline in w_{ij} diminishes monotonically as d_{ij} increases. In the second case, as in the parameterization shown in Equation 4.2, the rate of decline of w_{ij} initially increases with d_{ij} and then diminishes. In comparison to the weighting factors shown in Equation 4.2 the second case has a more pronounced "shoulder" and is closer in character to a step function. Appendix C.4 includes a graphical comparison of the different forms of the weighting factor. The results from using the alternative weighting factors are consistent with our earlier findings. In particular, in both cases $\lambda_h < \lambda_n < 0$, $\alpha_h > \alpha_n > 0$ and $\mu < 0$. With the exception of α_h and λ_h in the first case, all the relevant coefficients are statistically significant at the 10% level.

As a final investigation of our choice of weighting factors, we estimated a simplified model that excluded the Herfindahl index of brand counts and in the place of the hypermart and non-hypermart counts included the unweighted counts of hypermarts and non-hypermarts present between zero and one mile of the gas station of interest, between one and two miles of the gas station of interest and between two and three miles of the gas station of interest. Results from estimating the model following this approach (the "distance ring model") using ordinary least squares are shown in Appendix C.5.

Table 4.5 summarizes selected results from the distance ring model and compares them to the equivalent values using the original model. In order to calculate values that can be compared to the coefficients of the unweighted counts of hypermarts and non-hypermarts generated by the distance ring model, we used the values of λ_h, α_h, λ_n and α_n estimated earlier and values of d_{ij} that divided the appropriate distance rings into two parts with equal areas. On this basis, to generate an estimated price impact from the original model corresponding to the zero to one mile ring $d_{ij} = \sqrt{1/2}$ miles was used. The corresponding value for the one to two mile ring was $d_{ij} = \sqrt{5/2}$ miles and for the two to three mile ring it was $d_{ij} = \sqrt{13/2}$ miles.

Table 4.5

Comparison of Results from Distance Ring Model and Original Model

	Estimated price impact of an additional gas station:	
	Based on distance ring model	Based on original model
Hypermarts 0 to 1 mile	-0.0050 (0.0058)	-0.0122
Hypermarts 1 to 2 miles	-0.0074 (0.0041)	-0.0076
Hypermarts 2 to 3 miles	-0.0062 (0.0032)	-0.0030
Non-hypermarts 0 to 1 mile	-0.0033 (0.0014)	-0.0035
Non-hypermarts 1 to 2 miles	-0.0012 (0.0007)	-0.0009
Non- hypermarts 2 to 3 miles	0.0007 (0.0005)	-0.0001

Standard errors are indicated in parentheses.

If for each gas station type and distance ring we take as our null hypothesis that the price impact based on the original model is the true price impact, using the results of the distance ring model, none of the null hypotheses can be rejected at the 10% level using a two-tailed test.

4.8.3 Spatial Autoregression

As a further robustness check of our findings we estimated an autoregressive spatial model as shown in Equation 4.6.

$$\begin{aligned} p_i &= X_i\beta + (\text{hypermart count}_i)\lambda_h + (\text{non}-\text{hypermart count}_i)\lambda_n \\ &+ Log(\text{Herfindahl Index of brand counts}_i)\mu + u_i \\ &\text{where } u = \rho Mu + \varepsilon \qquad (4.6) \end{aligned}$$

This model allows for residual spatial effects in the error terms. If residual spatial effects are in fact present, the coefficients estimated using our earlier model will be consistent but the estimates of standard errors will be incorrect and consequently inferences based on the results from the model could be erroneous. Residual spatial effects would be present if the model omits a relevant variable that is itself spatially correlated such as demand characteristics that were incompletely captured by the control variables included in the original model. In Equation 4.6 M is a square matrix of the same dimension as the number of gas stations with a zero diagonal. We assumed that the off-diagonal elements of M have the same form as w_{ij} shown in Equation 4.2. We chose the corresponding distance normalization factor (we designate this value α_u) to minimize the calculated sum of squared residuals. We estimated the coefficients in the autoregressive spatial model using the generalized method of moments technique described in Kelejian and Prucha

(1999).[20] In estimating the autoregressive model, we used the values of α_h and α_n estimated using our original model.

Appendix C.6 shows the results from estimating the autoregressive spatial model using road distances, Euclidean distances and travel times. As discussed above, in each case the value of α_u was chosen so as to minimize the sum of squared residuals. In the model using road distances this value was 0.33. The corresponding value of ρ was estimated to be 0.0007. Taken together, the estimated value of ρ and the value of α_u that minimized the calculated sum of squared residuals suggest that any residual spatial effects are small in magnitude and are limited in geographic scope. Consistent with this observation, the coefficient values and the corresponding standard errors calculated using the autoregressive spatial model are not materially different from those calculated earlier using our original model. We interpret this as implying that our choice of explanatory variables and the associated choices of weighting factors largely capture the spatial characteristics of prices. It should be noted that this conclusion is predicated on M having the correct structure. A comparison of the results shown in Appendix C.6 shows that this conclusion holds for all of our measures of distance.

4.8.4 Common Ownership of Stations

In order to investigate the possible impact of common ownership on prices, we collected information about the ownership of the gas stations in our data set from the Arizona Department of Weights and Measures ("ADWM") and the Arizona Department of

[20] Bell and Bockstael (2000) is an early example of an application of this technique to micro level data.

Environmental Quality ("ADEQ"). These state authorities have responsibility for monitoring compliance with certain consumer and environmental laws and in this capacity they maintain records that are available for public inspection which include information about gas stations. In general we found the ADEQ data to be the more useful for our purposes and in most cases we relied on this source which we augmented by the ADWM data in the event of ambiguities or missing information. All gas stations in Arizona are required to obtain a permit to operate underground storage tanks. ADEQ maintains a directory of locations that have obtained such permits which includes the identity of the owner of the site. It should be noted however that the stated owner is not necessarily the ultimate economic owner. It could, for example, be the case that two stations which have different corporate owners are in fact under common control via an entity that owns both of the disclosed owners. Using the information from ADEQ and ADWM we identified a total of 17 ownership groups for the gas stations in our data set. 38 gas stations did not appear to be part of any ownership group. Details of the ownership groups are shown in Appendix C.7.

Using the ownership information, we estimated a revised version of the model (the "3rd adapted model") by adding an additional variable; the log of the Herfindahl index of ownership group counts. This new variable was calculated in the same way as the Herfindahl index of brand counts discussed earlier except ownership groups rather than brands were used to differentiate between gas stations. For the purposes of calculating the Herfindahl index of ownership group counts, a single distance normalization factor, α_{og}, was applied to all gas stations irrespective of their brands. The results from following this approach are shown in Appendix C.7.

As can be observed from Appendix C.7, when the log of the Herfindahl index of ownership group counts is included in the model its coefficient and the coefficient for the log of the Herfindahl index of brand counts are not statistically significantly different from zero. The same is true of α_{og}. It appears that, in the manner we are currently measuring it, common ownership has no discernable impact on prices that is not already reflected by the Herfindahl index of brand counts. We hypothesize two explanations for this finding. First, as discussed earlier, the information we have concerning ownership is incomplete and may not always reflect whether or not gas stations are under common ownership. Second, as discussed in Section 4.3, gas stations can be operated under a number of different contractual arrangements and therefore it may be the case that common ownership is simply not indicative of the likelihood of pricing coordination among gas stations. For example, although all other things being equal we might expect gas stations that are owned and operated by the same refiner to coordinate pricing, this would not be the case if the stations are leased to separate independent operators that are individually responsible for pricing polices. Since at present we have no information about lease arrangements we are unable to investigate this issue further.

On balance, the results of the alternative models discussed in this section encourage us to believe that the approach we are taking is reasonable and that the finding we reported in Section 4.7 are robust.

4.9 Conclusions

Our analysis shows that the combined impact of the locations and the brands of retail outlets matter when analyzing market prices.

We find that prices increase when the density of outlets falls, consistent with prior work. Applying our new method of flexible weighting factors, we are able to show how the impact on prices of an additional station varies with distance, while avoiding the need to use arbitrary predetermined market sizes. Using flexible weighting factors makes clear that the effect of hypermarts is greater in magnitude and extends over a larger distance than representative non-hypermart gas stations. This suggests that the low-price strategy followed by hypermarts and the attractiveness of their affiliated stores intensifies price competition locally leading to lower equilibrium prices over a wider area than is the case for other types of gas stations.

We demonstrate that, in the market we analyze, increased brand diversity as measured by the Herfindahl index of brand counts is associated with higher prices. This is consistent with brand loyalty having a greater effect on equilibrium prices than brand competition. We are not aware of other researchers investigating this issue. This finding could be relevant in the context of anti-trust assessments since it implies that an increase in the relative presence of a particular brand of outlet is not necessarily associated with price increases as might instinctively be expected. Although we make no claims as regards to consumer welfare, our finding might make a policymaker evaluating a possible business transaction that would lead to a reduction in brand diversity more optimistic about the likely market implications than would otherwise be the case.

Our conclusions do not change based on the distance metric used. Although this is an observation regarding a single market, it should give some comfort to researchers investigating similar issues who are unable to check the robustness of their finding to alternative distance metrics.

APPENDIX A

SUPPLEMENTARY MATERIALS FOR CHAPTER 2

A.1: Participants' Initial Endowments

Table 2.5

Initial Endowments by Trader Types

	Trader type		
	A	B	C
# units of asset	1	2	3
Initial value	$3.00	$6.00	$9.00
Cash	$12.50	$9.50	$6.50
Endowment value	$15.50	$15.50	$15.50

Table 2.6

Mix of Trader Types

	Liquidity level		
	High	Medium	Low
# type A traders	3	0	0
# type B traders	3	6	3
# type C traders	3	3	6

Table 2.7

Combined Initial Endowments

Asset type D = decreasing I = increasing	D	I	D	I	D	I
Liquidity level	High	High	Medium	Medium	Low	Low
# participants	9	9	9	9	9	9
# units of asset	18	18	21	21	24	24
Initial value	$54.00	$54.00	$63.00	$63.00	$72.00	$72.00
Total cash	$85.50	$85.50	$76.50	$76.50	$67.50	$67.50
Total value	$139.50	$139.50	$139.50	$139.50	$139.50	$139.50

A.2: Expected Liquidity Trends

Table 2.8

Expected Period-by-Period Liquidity

Asset type D = decreasing I = increasing	D	I	D	I	D	I
Liquidity level	High	High	Medium	Medium	Low	Low
Period						
1	61.3%	61.3%	54.8%	54.8%	48.4%	48.4%
2	63.9%	58.7%	57.8%	51.8%	51.8%	44.9%
3	66.5%	56.1%	60.9%	48.8%	55.3%	41.5%
4	69.0%	53.5%	63.9%	45.8%	58.7%	38.1%
5	71.6%	51.0%	66.9%	42.8%	62.2%	34.6%
6	74.2%	48.4%	69.9%	39.8%	65.6%	31.2%
7	76.8%	45.8%	72.9%	36.8%	69.0%	27.7%
8	79.4%	43.2%	75.9%	33.8%	72.5%	24.3%
9	81.9%	40.6%	78.9%	30.8%	75.9%	20.9%
10	84.5%	38.1%	81.9%	27.7%	79.4%	17.4%
11	87.1%	35.5%	84.9%	24.7%	82.8%	14.0%
12	89.7%	32.9%	88.0%	21.7%	86.2%	10.5%
13	92.3%	30.3%	91.0%	18.7%	89.7%	7.1%
14	94.8%	27.7%	94.0%	15.7%	93.1%	3.7%
15	97.4%	25.2%	97.0%	12.7%	96.6%	0.2%

Table 2.9

Expected Period-by-Period Average Cash Per Participant / Asset Holding Value

Asset type D = decreasing I = increasing	D	I	D	I	D	I
Liquidity level	High	High	Medium	Medium	Low	Low
Period						
1	3.17	3.17	2.83	2.83	2.50	2.50
2	3.54	2.84	3.20	2.51	2.87	2.18
3	3.96	2.56	3.63	2.23	3.29	1.89
4	4.46	2.31	4.13	1.97	3.79	1.64
5	5.05	2.08	4.71	1.75	4.38	1.41
6	5.75	1.88	5.42	1.54	5.08	1.21
7	6.61	1.69	6.28	1.36	5.94	1.02
8	7.69	1.52	7.35	1.19	7.02	0.86
9	9.07	1.37	8.74	1.04	8.40	0.70
10	10.92	1.23	10.58	0.90	10.25	0.56
11	13.50	1.10	13.17	0.77	12.83	0.43
12	17.38	0.98	17.04	0.65	16.71	0.31
13	23.83	0.87	23.50	0.54	23.17	0.20
14	36.75	0.77	36.42	0.43	36.08	0.10
15	75.50	0.67	75.17	0.34	74.83	0.01

A.3: Instructions for Experiment

Note the following instructions relate to a treatment with increasing-value assets. In treatments using decreasing-value assets the instructions contained minor differences reflecting the differences in dividends, maintenance fees and liquidation payments.

Instructions for Experiment

General

This is an experiment in the economics of market decision making. The instructions are simple and if you follow them carefully and make good decisions, you might earn a certain amount of money, which will be paid to you in cash at the end of the experiment. The experiment will last approximately one hour. Please do not speak with any other participants during this experiment.

Market Description

During the experiment you will have the opportunity to use the computer to buy and sell in a market. At the beginning of the experiment you will have an endowment of goods (called asset A) and cash. Once the experiment begins, tables in the right hand region of your computer screen will indicate to you the number of units of asset A and the amount of cash you have been allocated. These tables will be automatically updated by the computer during the experiment to show your current cash balance and inventory of asset A.

The experiment will consist of fifteen trading periods. In each period you may buy or sell units of asset A. Asset A can be considered to be an asset with a life of fifteen periods. Your inventory of asset A and cash carries over from one period to the next. Each period will last for two minutes. A counter in the upper right corner of your computer screen will indicate the current period and the time remaining in the current period.

At the end of each period, each unit of asset A will either pay you a dividend or require you to pay a maintenance fee. The dividend or maintenance fee will be decided randomly by the computer. The probabilities of different dividends or maintenance fees for each unit of asset A are indicated in the table below.

Probability	Dividend or Maintenance Fee
25%	10¢ dividend paid to you
25%	10¢ maintenance fee charged to you
25%	30¢ maintenance fee charged to you
25%	50¢ maintenance fee charged to you

From the information shown in the table it follows that on average a maintenance fee of 20¢ will be charged for each unit of asset A held by you at the end of each period. In any particular period the dividend paid or maintenance fee charged will be the same for all the units of asset A. The dividend and maintenance fee draws for each period are independent. This means that the probability of a particular dividend or maintenance fee at the end of any period is not affected by the dividend or maintenance fee in any previous period.

At the end of each period a message on your computer screen will indicate what dividend or maintenance fee will be charged. At this point your cash balance will be updated appropriately.

At the end of period 15, in addition to paying a dividend or charging a maintenance fee, each unit of asset A you own will pay you a liquidation payment of $6.00.

Buying and Selling Units

To buy units of asset A you must have cash to pay for them. Buying a unit reduces your cash balance by the purchase price. You may sell any units of asset A you have. Selling a unit increases your cash balance by the sale price.

If you wish to submit a proposal to buy a unit of asset A (this is called a “bid”) click on “buyer actions” in the lower left region of your screen, enter the price in the white area and click on “bid”.

If you wish to submit a proposal to sell a unit of asset A (this is called an “ask”) click on “seller actions” in the lower left region of your screen, enter the price in the white area and click on “ask”.

When you submit a bid (a proposal to buy), the computer checks if your bid price is higher than the existing best bid and if you have enough cash to pay for the purchase. If both the answers are affirmative, the current best bid is replaced by your bid in the area marked best bid in the upper left region of your screen.

When you submit an ask (a proposal to sell), the computer checks if your ask price is less than the existing best ask and if you own at least one unit of asset A. If both the answers are affirmative, the current best ask is replaced by your ask in the area marked best bid in the upper left region of your screen.

You can buy a unit of asset A in two different ways. First, you can submit a bid and wait for someone to accept it. Second, if you see a best ask price which you would like to accept click on “buyer actions” and then click on “buy” in the lower central region of your screen.

Similarly, you can sell a unit of asset A in two different ways. First, you can submit an ask and wait for someone to accept it. Second, if you see a best bid price which you would like to accept click on “seller actions” and then click on “sell” in the lower central region of your screen.

If you buy or sell a unit of asset A, the number of units you hold and your cash balance will be updated automatically by the computer.

The band along the lower edge of your screen indicates the prices at which recent trades for units of asset A have taken place. Information on up to the six most recent transactions that have occurred in the current period are shown with the most recent transaction on the left hand side.

In this experiment there is no order book or queue. When a better bid or offer replaces an unaccepted bid or offer the latter is flushed from the system. It does not stay in the memory. Similarly, once a transaction occurs any outstanding bid or ask is canceled.

During each period, so long as you have sufficient units of asset A and enough cash, you may buy and sell units as often as you wish. However, you are not required to buy or sell any units.

Average Holding Value Table

You can use the table on the final page of these instructions to help you to make decisions. There are six columns in the table. The first column, labeled Ending period, indicates the last trading period of the experiment. The second column, labeled Current period, indicated the period during which the average holding value is being calculated. The third column, labeled Number of holding periods, gives the number of holding periods from the period in the second column until the end of the experiment. The fourth column, labeled Average dividend/maintenance fee per period, gives the average amount of the dividend or maintenance fee in each period for each unit held in your inventory. The fifth column, labeled Liquidation payment, indicates the value of the liquidation payment that you will receive for each unit you hold at the end of period 15. The sixth column, labeled Average holding value per unit of inventory, gives the expected total value of the dividends or maintenance fees for the remainder of the experiment plus the liquidation fee. That is, for each unit you hold in your inventory for the remainder of the experiment, you receive on average the amount listed in column 6. The number in column 6 is calculated by multiplying the numbers in columns 3 and 4 and adding the number in column 5.

For example, suppose that it is currently period 9 and therefore there are 7 holding periods remaining. Since there is a 25% chance that a dividend of 10¢ is paid, a 25% chance that a maintenance fee of 10¢ is charged, a 25% chance that a maintenance fee of 30¢ is charged and a 25% chance that a maintenance fee of 50¢ is charged, on average there is a maintenance fee of 20¢ per period for each unit of asset A. If you hold a unit of asset A for seven periods, the total maintenance fee charged on the unit over the seven periods plus the liquidation payment received at the end of period 15 is on average \$4.60. (This is the case since $7\text{x}(-20¢) + \$6.00 = \$4.60$.)

Your Payment

The payment you will receive is equal to your cash balance at the end of period 15 plus a \$5.00 show up fee. Your cash balance at the end of period 15 will be automatically calculated by the computer and is equal to your initial cash balance plus all dividends you receive, minus all maintenance fees charged to you, minus cash you spend on the purchases of units, plus cash you receive from the sales of units, plus liquation payments you receive for units you hold at the end of period 15.

Review Questions

Q: How many trading periods will there be and how long will each period last?

A: There will be 15 periods. Each period will last two minutes. A counter in the upper right corner of your screen will indicate the current period and the time remaining.

Q: How do I know my cash balance and inventory of asset A?

A: They will be shown in the tables in the right hand region of your computer screen.

Q: What is a bid?

A: A proposal to buy a unit of asset A. To submit a bid click on "buyer actions" in the lower left region of your screen, enter the price in the white area and click on "bid".

Q: What is an ask?

A: A proposal to sell a unit of asset A. To submit an ask click on "seller actions" in the lower left region of your screen, enter the price in the white area and click on "ask".

Q: How do I know the current best bid and best ask?

A: They are shown in the upper left region of your screen labeled best bid and best ask.

Q: How can I buy a unit of asset A?

A: You can submit a bid and wait for someone to accept it or you can accept the best ask by clicking on "buyer actions" and then clicking on "buy".

Q: How can I sell a unit of asset A?

A: You can submit an ask and wait for someone to accept it or you can accept the best bid by clicking on "seller actions" and then clicking on "sell".

Q: In this experiment is there an order book or queue?

No. When a better bid or offer replaces an unaccepted bid or offer the latter is cancelled. Also, once a transaction occurs any outstanding bid or ask is canceled.

Q: Where can I find the average holding value per unit of asset A?

A: In the table at the end of these instructions.

Starting the Experiment

When you are ready to start the experiment, enter your work station number in the sign in screen on your computer in the area marked userID and click on enter. No password is required. Your work station number is indicated on the card attached to the barrier behind your computer terminal.

If some participants have not yet signed in a message indicating that you are waiting for the session to start signal from the server will appear on your screen.

Once all the participants have signed in the experiment will begin.

Average Holding Value Table

Ending period	Current period	Number of holding periods	x	Average dividend/ maintenance fee per period	+	Liquidation payment	=	Average holding value per unit of inventory
15	1	15		-20¢		$6.00		$3.00
15	2	14		-20¢		$6.00		$3.20
15	3	13		-20¢		$6.00		$3.40
15	4	12		-20¢		$6.00		$3.60
15	5	11		-20¢		$6.00		$3.80
15	6	10		-20¢		$6.00		$4.00
15	7	9		-20¢		$6.00		$4.20
15	8	8		-20¢		$6.00		$4.40
15	9	7		-20¢		$6.00		$4.60
15	10	6		-20¢		$6.00		$4.80
15	11	5		-20¢		$6.00		$5.00
15	12	4		-20¢		$6.00		$5.20
15	13	3		-20¢		$6.00		$5.40
15	14	2		-20¢		$6.00		$5.60
15	15	1		-20¢		$6.00		$5.80

A.4: Period-by-Period Trading Statistics

Decreasing-Value Asset High Liquidity (*DH*)

Period	Holding value	Volume	Mean price	Mean excess pricing	Total excess pricing	Total excess pricing per trader	Total excess pricing per asset
1	$3.00	5	$3.80	$0.80	$4.01	$0.45	$0.22
2	$2.80	8	$3.98	$1.18	$9.43	$1.05	$0.52
3	$2.60	11	$3.24	$0.64	$7.03	$0.78	$0.39
4	$2.40	7	$4.04	$1.64	$11.50	$1.28	$0.64
5	$2.20	12	$5.40	$3.20	$38.35	$4.26	$2.13
6	$2.00	7	$5.31	$3.31	$23.20	$2.58	$1.29
7	$1.80	5	$4.90	$3.10	$15.50	$1.72	$0.86
8	$1.60	4	$5.30	$3.70	$14.78	$1.64	$0.82
9	$1.40	8	$4.46	$3.06	$24.45	$2.72	$1.36
10	$1.20	5	$5.41	$4.21	$21.05	$2.34	$1.17
11	$1.00	6	$4.11	$3.11	$18.64	$2.07	$1.04
12	$0.80	3	$3.07	$2.27	$6.82	$0.76	$0.38
13	$0.60	6	$1.97	$1.37	$8.20	$0.91	$0.46
14	$0.40	6	$2.31	$1.91	$11.45	$1.27	$0.64
15	$0.20	9	$0.86	$0.66	$5.92	$0.66	$0.33
		Results for all periods		$2.16	$220.33	$24.48	$12.24

Increasing-Value Asset High Liquidity (*IHA*)

Period	Holding value	Volume	Mean price	Mean excess pricing	Total excess pricing	Total excess pricing per trader	Total excess pricing per asset
1	$3.00	5	$3.70	$0.70	$3.50	$0.39	$0.19
2	$3.20	6	$3.94	$0.74	$4.41	$0.49	$0.25
3	$3.40	3	$3.56	$0.16	$0.49	$0.05	$0.03
4	$3.60	5	$3.59	($0.01)	($0.05)	($0.01)	($0.00)
5	$3.80	7	$3.46	($0.34)	($2.40)	($0.27)	($0.13)
6	$4.00	3	$2.58	($1.42)	($4.26)	($0.47)	($0.24)
7	$4.20	5	$2.58	($1.62)	($8.11)	($0.90)	($0.45)
8	$4.40	4	$1.61	($2.79)	($11.15)	($1.24)	($0.62)
9	$4.60	7	$1.58	($3.02)	($21.16)	($2.35)	($1.18)
10	$4.80	4	$1.38	($3.42)	($13.67)	($1.52)	($0.76)
11	$5.00	3	$1.15	($3.85)	($11.55)	($1.28)	($0.64)
12	$5.20	5	$1.54	($3.66)	($18.31)	($2.03)	($1.02)
13	$5.40	6	$1.15	($4.25)	($25.48)	($2.83)	($1.42)
14	$5.60	5	$0.59	($5.01)	($25.04)	($2.78)	($1.39)
15	$5.80	1	$0.80	($5.00)	($5.00)	($0.56)	($0.28)
		Results for all periods		($2.00)	($137.79)	($15.31)	($7.65)

Decreasing-Value Asset Medium Liquidity (*DM*)

Period	Holding value	Volume	Mean price	Mean excess pricing	Total excess pricing	Total excess pricing per trader	Total excess pricing per asset
1	$3.00	5	$5.32	$2.32	$11.60	$1.29	$0.55
2	$2.80	7	$3.64	$0.84	$5.91	$0.66	$0.28
3	$2.60	9	$3.86	$1.26	$11.35	$1.26	$0.54
4	$2.40	9	$3.95	$1.55	$13.91	$1.55	$0.66
5	$2.20	13	$3.94	$1.74	$22.66	$2.52	$1.08
6	$2.00	10	$2.73	$0.73	$7.30	$0.81	$0.35
7	$1.80	9	$4.33	$2.53	$22.80	$2.53	$1.09
8	$1.60	7	$3.88	$2.28	$15.93	$1.77	$0.76
9	$1.40	12	$2.30	$0.90	$10.84	$1.20	$0.52
10	$1.20	10	$1.25	$0.05	$0.50	$0.06	$0.02
11	$1.00	3	$1.02	$0.02	$0.05	$0.01	$0.00
12	$0.80	6	$0.83	$0.03	$0.20	$0.02	$0.01
13	$0.60	4	$0.67	$0.07	$0.27	$0.03	$0.01
14	$0.40	7	$0.55	$0.15	$1.06	$0.12	$0.05
15	$0.20	14	$0.23	$0.03	$0.36	$0.04	$0.02
		Results for all periods		$1.00	$124.74	$13.86	$5.94

Increasing-Value Asset Medium Liquidity (*IM*)

Period	Holding value	Volume	Mean price	Mean excess pricing	Total excess pricing	Total excess pricing per trader	Total excess pricing per asset
1	$3.00	7	$2.54	($0.46)	($3.25)	($0.36)	($0.15)
2	$3.20	10	$3.95	$0.75	$7.50	$0.83	$0.36
3	$3.40	4	$3.53	$0.13	$0.50	$0.06	$0.02
4	$3.60	10	$3.26	($0.35)	($3.45)	($0.38)	($0.16)
5	$3.80	10	$3.42	($0.39)	($3.85)	($0.43)	($0.18)
6	$4.00	5	$3.79	($0.21)	($1.06)	($0.12)	($0.05)
7	$4.20	6	$3.56	($0.64)	($3.84)	($0.43)	($0.18)
8	$4.40	8	$3.72	($0.68)	($5.46)	($0.61)	($0.26)
9	$4.60	9	$3.60	($1.00)	($8.96)	($1.00)	($0.43)
10	$4.80	4	$3.83	($0.97)	($3.88)	($0.43)	($0.18)
11	$5.00	0	n/a	n/a	n/a	n/a	n/a
12	$5.20	1	$3.30	($1.90)	($1.90)	($0.21)	($0.09)
13	$5.40	0	n/a	n/a	n/a	n/a	n/a
14	$5.60	1	$3.30	($2.30)	($2.30)	($0.26)	($0.11)
15	$5.80	0	n/a	n/a	n/a	n/a	n/a
		Results for all periods		($0.40)	($29.95)	($3.33)	($1.43)

Decreasing-Value Asset Low Liquidity (*DL*)

Period	Holding value	Volume	Mean price	Mean excess pricing	Total excess pricing	Total excess pricing per trader	Total excess pricing per asset
1	$3.00	7	$1.09	($1.91)	($13.40)	($1.49)	($0.56)
2	$2.80	11	$1.45	($1.35)	($14.82)	($1.65)	($0.62)
3	$2.60	5	$1.12	($1.48)	($7.40)	($0.82)	($0.31)
4	$2.40	5	$1.54	($0.86)	($4.28)	($0.48)	($0.18)
5	$2.20	4	$2.65	$0.45	$1.81	$0.20	$0.08
6	$2.00	6	$2.25	$0.25	$1.48	$0.16	$0.06
7	$1.80	11	$2.46	$0.66	$7.23	$0.80	$0.30
8	$1.60	3	$2.26	$0.66	$1.99	$0.22	$0.08
9	$1.40	6	$2.08	$0.68	$4.10	$0.46	$0.17
10	$1.20	1	$2.00	$0.80	$0.80	$0.09	$0.03
11	$1.00	3	$1.95	$0.95	$2.84	$0.32	$0.12
12	$0.80	4	$1.84	$1.04	$4.15	$0.46	$0.17
13	$0.60	5	$1.70	$1.10	$5.49	$0.61	$0.23
14	$0.40	5	$1.38	$0.98	$4.91	$0.55	$0.20
15	$0.20	5	$0.28	$0.08	$0.40	$0.04	$0.02
		Results for all periods		($0.06)	($4.70)	($0.52)	($0.20)

Increasing-Value Asset Low Liquidity (*ILA*)

Period	Holding value	Volume	Mean price	Mean excess pricing	Total excess pricing	Total excess pricing per trader	Total excess pricing per asset
1	$3.00	7	$2.32	($0.68)	($4.75)	($0.53)	($0.20)
2	$3.20	9	$3.06	($0.14)	($1.30)	($0.14)	($0.05)
3	$3.40	12	$3.29	($0.11)	($1.30)	($0.14)	($0.05)
4	$3.60	11	$2.36	($1.24)	($13.68)	($1.52)	($0.57)
5	$3.80	12	$1.99	($1.81)	($21.70)	($2.41)	($0.90)
6	$4.00	11	$2.07	($1.93)	($21.20)	($2.36)	($0.88)
7	$4.20	7	$2.11	($2.09)	($14.60)	($1.62)	($0.61)
8	$4.40	6	$2.42	($1.98)	($11.90)	($1.32)	($0.50)
9	$4.60	10	$2.20	($2.40)	($23.97)	($2.66)	($1.00)
10	$4.80	2	$2.74	($2.06)	($4.12)	($0.46)	($0.17)
11	$5.00	5	$2.17	($2.83)	($14.15)	($1.57)	($0.59)
12	$5.20	1	$2.20	($3.00)	($3.00)	($0.33)	($0.13)
13	$5.40	5	$2.18	($3.22)	($16.10)	($1.79)	($0.67)
14	$5.60	1	$1.90	($3.70)	($3.70)	($0.41)	($0.15)
15	$5.80	5	$1.28	($4.52)	($22.61)	($2.51)	($0.94)
		Results for all periods		($1.71)	($178.07)	($19.79)	($7.42)

Increasing-Value Asset High Liquidity (*IHB*)

Period	Holding value	Volume	Mean price	Mean excess pricing	Total excess pricing	Total excess pricing per trader	Total excess pricing per asset
1	$3.00	4	$3.69	$0.69	$2.75	$0.31	$0.15
2	$3.20	7	$3.77	$0.57	$4.00	$0.44	$0.22
3	$3.40	7	$3.25	($0.15)	($1.05)	($0.12)	($0.06)
4	$3.60	9	$2.62	($0.98)	($8.85)	($0.98)	($0.49)
5	$3.80	9	$2.92	($0.88)	($7.95)	($0.88)	($0.44)
6	$4.00	5	$2.78	($1.22)	($6.10)	($0.68)	($0.34)
7	$4.20	5	$2.91	($1.29)	($6.45)	($0.72)	($0.36)
8	$4.40	6	$2.81	($1.59)	($9.55)	($1.06)	($0.53)
9	$4.60	8	$2.86	($1.74)	($13.90)	($1.54)	($0.77)
10	$4.80	5	$2.85	($1.95)	($9.75)	($1.08)	($0.54)
11	$5.00	4	$2.81	($2.19)	($8.75)	($0.97)	($0.49)
12	$5.20	4	$2.63	($2.57)	($10.27)	($1.14)	($0.57)
13	$5.40	4	$2.67	($2.73)	($10.93)	($1.21)	($0.61)
14	$5.60	2	$3.03	($2.58)	($5.15)	($0.57)	($0.29)
15	$5.80	2	$2.93	($2.88)	($5.75)	($0.64)	($0.32)
		Results for all periods		($1.21)	($97.70)	($10.86)	($5.43)

Increasing-Value Asset High Liquidity (*IHC*)

Period	Holding value	Volume	Mean price	Mean excess pricing	Total excess pricing	Total excess pricing per trader	Total excess pricing per asset
1	$3.00	4	$4.75	$1.75	$7.00	$0.78	$0.39
2	$3.20	10	$2.45	($0.75)	($7.50)	($0.83)	($0.42)
3	$3.40	12	$2.48	($0.92)	($11.06)	($1.23)	($0.61)
4	$3.60	11	$2.13	($1.47)	($16.15)	($1.79)	($0.90)
5	$3.80	10	$1.57	($2.23)	($22.26)	($2.47)	($1.24)
6	$4.00	11	$1.39	($2.61)	($28.70)	($3.19)	($1.59)
7	$4.20	14	$1.47	($2.73)	($38.25)	($4.25)	($2.12)
8	$4.40	17	$1.57	($2.83)	($48.14)	($5.35)	($2.67)
9	$4.60	18	$1.05	($3.55)	($63.86)	($7.10)	($3.55)
10	$4.80	20	$0.99	($3.81)	($76.26)	($8.47)	($4.24)
11	$5.00	13	$1.07	($3.93)	($51.04)	($5.67)	($2.84)
12	$5.20	10	$0.91	($4.30)	($42.95)	($4.77)	($2.39)
13	$5.40	4	$0.84	($4.56)	($18.25)	($2.03)	($1.01)
14	$5.60	7	$0.68	($4.92)	($34.42)	($3.82)	($1.91)
15	$5.80	8	$0.56	($5.24)	($41.93)	($4.66)	($2.33)
		Results for all periods		($2.92)	($493.77)	($54.86)	($27.43)

Increasing-Value Asset Low Liquidity (*ILB*)

Period	Holding value	Volume	Mean price	Mean excess pricing	Total excess pricing	Total excess pricing per trader	Total excess pricing per asset
1	$3.00	8	$1.69	($1.31)	($10.50)	($1.17)	($0.44)
2	$3.20	8	$1.84	($1.36)	($10.85)	($1.21)	($0.45)
3	$3.40	9	$1.39	($2.01)	($18.10)	($2.01)	($0.75)
4	$3.60	7	$1.96	($1.64)	($11.51)	($1.28)	($0.48)
5	$3.80	8	$2.37	($1.43)	($11.45)	($1.27)	($0.48)
6	$4.00	9	$2.40	($1.60)	($14.40)	($1.60)	($0.60)
7	$4.20	10	$2.48	($1.72)	($17.21)	($1.91)	($0.72)
8	$4.40	12	$2.41	($1.99)	($23.87)	($2.65)	($0.99)
9	$4.60	6	$2.22	($2.38)	($14.30)	($1.59)	($0.60)
10	$4.80	4	$2.57	($2.23)	($8.92)	($0.99)	($0.37)
11	$5.00	2	$2.48	($2.53)	($5.05)	($0.56)	($0.21)
12	$5.20	3	$2.27	($2.93)	($8.80)	($0.98)	($0.37)
13	$5.40	2	$2.24	($3.16)	($6.32)	($0.70)	($0.26)
14	$5.60	8	$1.98	($3.62)	($28.96)	($3.22)	($1.21)
15	$5.80	3	$1.53	($4.27)	($12.81)	($1.42)	($0.53)
		Results for all periods		($2.05)	($203.03)	($22.56)	($8.46)

Increasing-Value Asset Low Liquidity (*ILC*)

Period	Holding value	Volume	Mean price	Mean excess pricing	Total excess pricing	Total excess pricing per trader	Total excess pricing per asset
1	$3.00	5	$3.06	$0.06	$0.30	$0.03	$0.01
2	$3.20	2	$2.98	($0.23)	($0.45)	($0.05)	($0.02)
3	$3.40	5	$2.10	($1.30)	($6.51)	($0.72)	($0.27)
4	$3.60	4	$1.65	($1.95)	($7.80)	($0.87)	($0.33)
5	$3.80	2	$0.29	($3.51)	($7.02)	($0.78)	($0.29)
6	$4.00	6	$1.66	($2.34)	($14.03)	($1.56)	($0.58)
7	$4.20	3	$1.80	($2.40)	($7.20)	($0.80)	($0.30)
8	$4.40	1	$0.50	($3.90)	($3.90)	($0.43)	($0.16)
9	$4.60	0	n/a	n/a	n/a	n/a	n/a
10	$4.80	3	$0.81	($3.99)	($11.96)	($1.33)	($0.50)
11	$5.00	3	$0.50	($4.50)	($13.49)	($1.50)	($0.56)
12	$5.20	1	$0.30	($4.90)	($4.90)	($0.54)	($0.20)
13	$5.40	1	$0.05	($5.35)	($5.35)	($0.59)	($0.22)
14	$5.60	1	$0.50	($5.10)	($5.10)	($0.57)	($0.21)
15	$5.80	0	n/a	n/a	n/a	n/a	n/a
		Results for all periods		($2.36)	($87.41)	($9.71)	($3.64)

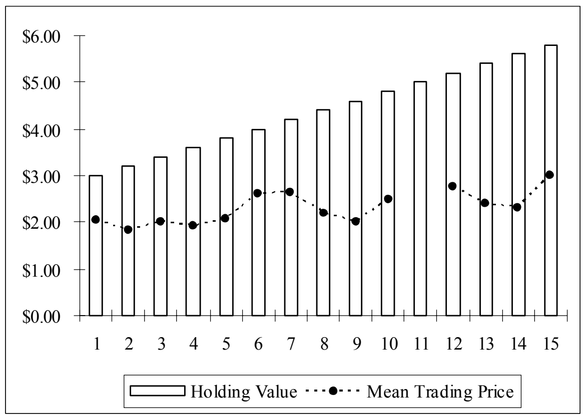
A.5: Results for Experimental Sessions IHZ and ILZ

Sessions IHZ and ILZ followed the same designs as the increasing-value asset high-liquidity and increasing-value asset low-liquidity treatments respectively described earlier except IHZ had seven participants and ILZ three participants. As a consequence of the different number of participants these sessions are not included in the discussion and analysis elsewhere in this chapter. The results of these two additional experimental sessions however do appear to be generally consistent with those of the other ten sessions.

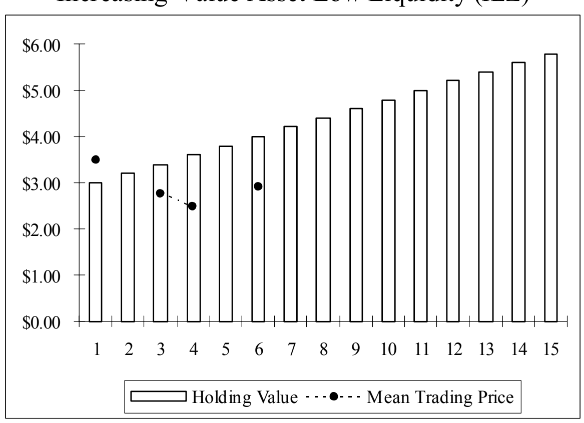
Figure 2.3

Summary Results for Sessions IHZ and ILZ

Increasing-Value Asset High Liquidity (*IHZ*)



Increasing-Value Asset Low Liquidity (*ILZ*)



Note: The absence of a point in a particular period indicates that no trades occurred in that period.

Session IHZ had seven participants and session ILZ had three participants.

Increasing-Value Asset High Liquidity (*IHZ*)

Period	Holding value	Volume	Mean price	Mean excess pricing	Total excess pricing	Total excess pricing per trader	Total excess pricing per asset
1	$3.00	4	$2.03	($0.97)	($3.89)	($0.56)	($0.32)
2	$3.20	6	$1.84	($1.36)	($8.15)	($1.16)	($0.68)
3	$3.40	6	$2.00	($1.40)	($8.38)	($1.20)	($0.70)
4	$3.60	7	$1.93	($1.67)	($11.67)	($1.67)	($0.97)
5	$3.80	6	$2.07	($1.73)	($10.40)	($1.49)	($0.87)
6	$4.00	7	$2.61	($1.39)	($9.75)	($1.39)	($0.81)
7	$4.20	3	$2.63	($1.57)	($4.72)	($0.67)	($0.39)
8	$4.40	8	$2.19	($2.21)	($17.70)	($2.53)	($1.47)
9	$4.60	2	$2.01	($2.60)	($5.19)	($0.74)	($0.43)
10	$4.80	3	$2.50	($2.30)	($6.90)	($0.99)	($0.58)
11	$5.00	0	n/a	n/a	n/a	n/a	n/a
12	$5.20	2	$2.75	($2.45)	($4.90)	($0.70)	($0.41)
13	$5.40	2	$2.40	($3.01)	($6.01)	($0.86)	($0.50)
14	$5.60	3	$2.30	($3.30)	($9.90)	($1.41)	($0.83)
15	$5.80	1	$3.00	($2.80)	($2.80)	($0.40)	($0.23)
		Results for all periods		($1.84)	($110.36)	($15.77)	($9.20)

Increasing-Value Asset Low Liquidity (*ILZ*)

Period	Holding value	Volume	Mean price	Mean excess pricing	Total excess pricing	Total excess pricing per trader	Total excess pricing per asset
1	$3.00	1	$3.50	$0.50	$0.50	$0.17	$0.06
2	$3.20	0	n/a	n/a	n/a	n/a	n/a
3	$3.40	1	$2.75	($0.65)	($0.65)	($0.22)	($0.08)
4	$3.60	1	$2.50	($1.10)	($1.10)	($0.37)	($0.14)
5	$3.80	0	n/a	n/a	n/a	n/a	n/a
6	$4.00	1	$2.90	($1.10)	($1.10)	($0.37)	($0.14)
7	$4.20	0	n/a	n/a	n/a	n/a	n/a
8	$4.40	0	n/a	n/a	n/a	n/a	n/a
9	$4.60	0	n/a	n/a	n/a	n/a	n/a
10	$4.80	0	n/a	n/a	n/a	n/a	n/a
11	$5.00	0	n/a	n/a	n/a	n/a	n/a
12	$5.20	0	n/a	n/a	n/a	n/a	n/a
13	$5.40	0	n/a	n/a	n/a	n/a	n/a
14	$5.60	0	n/a	n/a	n/a	n/a	n/a
15	$5.80	0	n/a	n/a	n/a	n/a	n/a
		Results for all periods		($0.59)	($2.35)	($0.78)	($0.29)

APPENDIX B

SUPPLEMENTARY MATERIALS FOR CHAPTER 3

B.1: Data Availability to Estimate Equation 3.3

Table 3.10

Data Availability to Estimate Equation 3.3

Category	Number of observations
A. No competing races in the defined time interval	101
B. One competing race	
1. runner participates in the competing race	0
2. runner does not participate	117
C. Two competing races	
1. runner participates in both competing races	0
2. runner participates in one	103
3. runner participates in neither	540
Total	861
Availability for estimating Equation 3.3	
Available (B2, C2 and C3)	760
Not available (A, B1 and C1)	101
Total	861

The table above indicates the number of observations that are available to estimate Equation 3.3 in light of the base case algorithm we chose to identify competing races.

B.2: Sorting Equation Robustness Checks

Table 3.11

Sorting Equation Results Using Alternative 1 Definition of Competing Races

Variable	Coefficient	Standard error	p value
Total value of prizes ($000s)	0.0768	0.0287	0.007
Herfindahl index of prize values	-2.926	2.304	0.204
Rank x Total value of prizes ($000s)	-0.0002888	0.0001587	0.069
Rank x Herfindahl index of prize values	0.016356	0.012015	0.173

Table 3.12

Sorting Equation Results Using Alternative 2 Definition of Competing Races

Variable	Coefficient	Standard error	p value
Total value of prizes ($000s)	0.0870	0.0321	0.007
Herfindahl index of prize values	-3.624	2.081	0.082
Rank x Total value of prizes ($000s)	-0.0003279	0.0001718	0.056
Rank x Herfindahl index of prize values	0.018140	0.010383	0.081

Table 3.13

Sorting Equation Results Including Number of Top Runners

Variable	Coefficient	Standard error	p value
Total value of prizes ($000s)	0.0853	0.0305	0.005
Herfindahl index of prize values	-0.806	2.491	0.746
Rank x Total value of prizes ($000s)	-0.0003524	0.0001482	0.017
Rank x Herfindahl index of prize values	0.006361	0.011121	0.567
Number of top runners	0.03572	0.01448	0.014

Table 3.14

Sorting Equation Results Using Only Prize-Winner Observations

Variable	Coefficient	Standard error	p value
Total value of prizes ($000s)	0.1545	0.0609	0.011
Herfindahl index of prize values	-3.788	4.710	0.421
Rank x Total value of prizes ($000s)	-0.002788	0.001462	0.057
Rank x Herfindahl index of prize values	-0.007334	0.056102	0.896

Table 3.15

Sorting Equation Results Using Only Non Prize-Winner Observations

Variable	Coefficient	Standard error	p value
Total value of prizes ($000s)	0.1493	0.0461	0.001
Herfindahl index of prize values	0.9112	3.5960	0.800
Rank x Total value of prizes ($000s)	-0.0004846	0.0002058	0.019
Rank x Herfindahl index of prize values	-0.0004835	0.0148308	0.974

B.3: Speed Equation Robustness Checks

Table 3.16

Speed Equation Results Omitting Runner Rankings

Variable	Coefficient	Standard error	p value
W_k (intrinsic race characteristics)			
Total value of prizes ($000s)	0.0139	0.00361	0.000
Herfindahl Index of prize values	-0.8430	0.1876	0.000
Race distance in km	-0.04205	0.00714	0.000
(Race distance in km)^2	0.0002597	0.0001155	0.028
Dummy for hilly course	-0.1628	0.0800	0.046
Dummy for down hill course	0.1595	0.0704	0.027
Dummy if course topography unknown	-0.01221	0.08907	0.891
Average temperature	-0.02659	0.02790	0.344
(Average temperature)^2	0.000227	0.000239	0.344
X_k (global competitive intensity)			
Number of top runners	-0.0000982	0.0035054	0.978
Y_{ik} (local competitive intensity)			
Number of top runners within 20 ranking places	0.04490	0.01673	0.009
Constant	6.281	0.809	0.000

The R squared for the regression is 0.54. Standard errors are adjusted for clustering by race.

Table 3.17

Speed Equation Results with Additional Interaction Terms

Variable	Coefficient	Standard error	p value
W_k (intrinsic race characteristics)			
Total value of prizes ($000s)	0.00322	0.00337	0.343
Herfindahl index of prize values	-0.7437	0.2009	0.000
Race distance in km	-0.03846	0.00654	0.000
(Race distance in km)^2	0.0002652	0.0001039	0.013
Dummy for hilly course	-0.1680	0.0593	0.006
Dummy for down hill course	0.1117	0.0460	0.018
Dummy if course topography unknown	0.02391	0.08089	0.768
Average temperature	-0.01680	0.02225	0.453
(Average temperature)^2	0.0001517	0.0001959	0.441
X_k (global competitive intensity)			
Number of top runners	0.003560	0.002200	0.110
Y_{ik} (local competitive intensity)			
Number of top runners within 20 ranking places	0.01932	0.01154	0.099
Z_i (personal characteristics of runner)			
Runner ranking	-0.003669	0.000364	0.000
Additional Interaction Variables			
Runner ranking x Total value of prizes ($000s)	8.79e-6	14.9e-6	0.558
Runner ranking x Herfindahl index of prizes	0.0005136	0.0009869	0.604
Constant	6.565	0.633	0.000

The R squared for the regression is 0.82. Standard errors are adjusted for clustering by race.

Table 3.18

Speed Equation Results Using Only Prize-Winner Observations

Variable	Coefficient	Standard error	p value
W_k (intrinsic race characteristics)			
Total value of prizes ($000s)	0.0126	0.0036	0.001
Herfindahl index of prize values	0.01511	0.29543	0.959
Race distance in km	-0.03581	0.00728	0.000
(Race distance in km)^2	0.0002408	0.0001249	0.058
Dummy for hilly course	-0.1626	0.0555	0.005
Dummy for down hill course	0.2685	0.0554	0.000
Dummy if course topography unknown	0.01012	0.05408	0.852
Average temperature	-0.008533	0.018153	0.640
(Average temperature)^2	0.0000795	0.0001563	0.613
X_k (global competitive intensity)			
Number of top runners	0.002157	0.004493	0.633
Y_{ik} (local competitive intensity)			
Number of top runners within 20 ranking places	-0.003311	0.008747	0.706
Z_i (personal characteristics of runner)			
Runner ranking	-0.002756	0.000263	0.000
Additional Interaction Variables			
Constant	6.186	0.517	0.000

The R squared for the regression is 0.87. Standard errors are adjusted for clustering by race.

Table 3.19

Speed Equation Results Using Only Non Prize-Winner Observations

Variable	Coefficient	Standard error	p value
W_k (intrinsic race characteristics)			
Total value of prizes ($000s)	0.00543	0.00281	0.058
Herfindahl index of prize values	-0.5908	0.2115	0.007
Race distance in km	-0.04058	0.00672	0.000
(Race distance in km)^2	0.0002853	0.0001060	0.009
Dummy for hilly course	-0.1757	0.0634	0.007
Dummy for down hill course	0.06392	0.05104	0.215
Dummy if course topography unknown	0.007593	0.09108	0.934
Average temperature	-0.01685	0.02527	0.507
(Average temperature)^2	0.0001471	0.0002210	0.508
X_k (global competitive intensity)			
Number of top runners	0.006734	0.002436	0.007
Y_{ik} (local competitive intensity)			
Number of top runners within 20 ranking places	0.02637	0.01582	0.100
Z_i (personal characteristics of runner)			
Runner ranking	-0.002871	0.000151	0.000
Additional Interaction Variables			
Constant	6.325	0.725	0.000

The R squared for the regression is 0.80. Standard errors are adjusted for clustering by race.

Table 3.20

Speed Equation Results Without Local Competitive Intensity

Variable	Coefficient	Standard error	p value
W_k (intrinsic race characteristics)			
Total value of prizes ($000s)	0.00530	0.00269	0.053
Herfindahl index of prize values	-0.6601	0.2209	0.004
Race distance in km	-0.03911	0.00682	0.000
(Race distance in km)^2	0.0002733	0.0001074	0.013
Dummy for hilly course	-0.1703	0.0601	0.006
Dummy for down hill course	0.1017	0.0482	0.039
Dummy if course topography unknown	0.02106	0.08259	0.799
Average temperature	-0.01594	0.02292	0.489
(Average temperature)^2	0.0001448	0.0002023	0.476
X_k (global competitive intensity)			
Number of top runners	0.005759	0.0024805	0.023
Z_i (personal characteristics of runner)			
Runner ranking	-0.003505	0.000130	0.000
Additional Interaction Variables			
Constant	6.528	0.661	0.000

The R squared for the regression is 0.82. Standard errors are adjusted for clustering by race.

Table 3.21

Speed Equation Results Using Runner Fixed Effects

Variable	Coefficient	Standard error	p value
W_k (intrinsic race characteristics)			
Total value of prizes ($000s)	0.00379	0.00131	0.004
Herfindahl index of prize values	0.1007	0.0736	0.172
Race distance in km	-0.02746	0.00193	0.000
(Race distance in km)^2	0.0001301	0.0000284	0.000
Dummy for hilly course	-0.1102	0.0208	0.000
Dummy for down hill course	0.1496	0.0339	0.000
Dummy if course topography unknown	0.04396	0.02152	0.042
Average temperature	-0.01543	0.00703	0.029
(Average temperature)^2	0.0001199	0.0000584	0.041
X_k (global competitive intensity)			
Number of top runners	0.001992	0.001317	0.131
Y_{ik} (local competitive intensity)			
Number of top runners within 20 ranking places	-0.001809	0.004296	0.674
Constant	5.679	0.214	0.000

B.4: Choice of Ranking Methodology Robustness Checks

Table 3.22

Sorting Equation Results Using Alternative Rankings Based on FE Analysis

Variable	Coefficient	Standard error	p value
Total value of prizes ($000s)	0.1394	0.0363	0.000
Herfindahl index of prize values	-3.580	3.162	0.258
Rank x Total value of prizes ($000s)	-0.0005614	0.0001788	0.002
Rank x Herfindahl index of prize values	0.01489	0.01205	0.216

Table 3.23

Sorting Equation Results Using "Ability" Based on FE Dummy Variable Coefficients Instead of Rankings

Variable	Coefficient	Standard error	p value
Total value of prizes ($000s)	0.1060	0.0269	0.000
Herfindahl index of prize values	-2.523	2.438	0.301
Ability x Total value of prizes ($000s)	0.1236	0.0384	0.001
Ability x Herfindahl index of prize values	-2.955	2.560	0.249

Note that the estimated fixed effects dummy variable coefficients used to produce the results shown in Table 3.23 range in value from -1.85 to 0.36 with a mean value of -0.57. Since a high value of the fixed effects dummy variable coefficient corresponds to a fast runner, we would expect the final two coefficients shown in Table 3.23 to be of opposite sign to the results produced using rankings where a fast runner is assigned a low ranking number.

Table 3.24

Speed Equation Results Using Alternative Rankings Based on FE Analysis

Variable	Coefficient	Standard error	p value
W_k (intrinsic race characteristics)			
Total value of prizes ($000s)	0.00271	0.00133	0.045
Herfindahl index of prize values	-0.01048	0.07344	0.887
Race distance in km	-0.02661	0.00263	0.000
(Race distance in km)^2	0.0001247	0.0000443	0.006
Dummy for hilly course	-0.1100	0.0228	0.000
Dummy for down hill course	0.1563	0.0346	0.000
Dummy if course topography unknown	0.04416	0.03342	0.191
Average temperature	-0.01475	0.00917	0.112
(Average temperature)^2	0.0001164	0.0000795	0.148
X_k (global competitive intensity)			
Number of top runners	0.002390	0.001183	0.047
Y_{ik} (local competitive intensity)			
Number of top runners within 20 ranking places	-0.003230	0.003806	0.399
Z_i (personal characteristics of runner)			
Runner ranking	-0.004731	0.000102	0.000
Additional Interaction Variables			
Constant	6.510	0.256	0.000

The R squared for the regression is 0.96. Standard errors are adjusted for clustering by race.

B.5: Counterfactual Analysis

Table 3.25

Probability of Defections to Race 8

Ranking	Probability
24	0.1778
27	0.1759
57	0.1566
71	0.1476
86	0.1379
87	0.1372
118	0.1170
136	0.1052
227	0.0449
260	0.0228
261	0.0221
294	0.0000
295	0.0000
296	0.0000
297	0.0000
355	0.0000
360	0.0000
363	0.0000

Table 3.25 shows the probability of runners originally in race 28 choosing to defect to race 8 at the hypothetical prize levels.

Table 3.26

Probability of Remaining in Race 8

Ranking	Probability
82	1.0000
282	1.0000
284	1.0000
310	0.9892
343	0.9670

Table 3.26 shows the probability of runners originally in race 8 choosing to remain in race 8 at the hypothetical prize levels.

Table 3.27

Incentive Effects for Race 8 Participants

(Effects are measured in meters per second)

Ranking	Direct effect	Indirect effect	Combined effect
82	0.01627	0.01223	0.02850
282	0.01627	0.00429	0.02056
284	0.01627	0.00429	0.02056
310	0.01627	0.00429	0.02056
343	0.01627	0.00429	0.02056

Table 3.27 shows the predicted impact of the hypothetical change in prizes on the speed of all the top runners already committed to race 8. Note that the runner ranked 82 was the first placed top runner with a time of 1,574 seconds. The race had a length of 8km and so this winning time corresponded to an average speed of 5.1 meters per second. For this runner the predicted combined incentive effect corresponds to an increase in speed of approximately 0.6%. The runner ranked 343 was the slowest of the top runners in this race with a time of 1,927 seconds. In this case the predicted combined incentive effect corresponds to an increase in speed of approximately 0.5%.

APPENDIX C

SUPPLEMENTARY MATERIALS FOR CHAPTER 4

C.1: Results Using Alternative Distances Metrics

Table 4.6

Results Using Euclidean Distances

	Coefficient value	s.e.	p value	90% confidence interval low	90% confidence interval high
Constant	1.994	0.009	0.000	1.979	2.009
Population density	2.911E-06	1.491E-06	0.051	4.585E-07	5.364E-06
Traffic flow	0.000172	0.000089	0.054	0.000025	0.000319
Hypermart	-0.026	0.012	0.037	-0.046	-0.005
Arco	-0.029	0.009	0.001	-0.043	-0.015
Chevron	0.072	0.007	0.000	0.060	0.083
Conoco	-0.011	0.009	0.197	-0.025	0.003
Citgo	0.034	0.011	0.003	0.015	0.052
Diamond Shamrock	-0.025	0.008	0.001	-0.038	-0.013
Exxon	0.044	0.010	0.000	0.027	0.061
Mobil	0.040	0.008	0.000	0.026	0.053
Shell	0.060	0.009	0.000	0.045	0.076
76	0.021	0.012	0.076	0.002	0.040
Texaco	0.059	0.013	0.000	0.038	0.080
Convenience store	-0.005	0.007	0.479	-0.018	0.007
Franchise food outlet	0.013	0.007	0.068	0.001	0.025
Car wash	0.004	0.009	0.653	-0.010	0.018
Repair shop	0.014	0.007	0.051	0.002	0.026
α hypermarts (α_h)	1.063	0.476	0.025	0.281	1.846
λ hypermarts (λ_h)	-0.013	0.006	0.037	-0.023	-0.003
α non-hypermarts (α_n)	0.698	0.172	0.000	0.415	0.980
λ non-hypermarts (λ_n)	-0.005	0.003	0.059	-0.009	-0.001
Log of HI of brand counts (μ)	-0.021	0.014	0.131	-0.044	0.002

Euclidean distances are measured in miles to the nearest foot.

Figure 4.2

Estimated Price Impact of Hypermart and Non-Hypermart Gas Stations Based on Euclidean Distance from Station of Interest

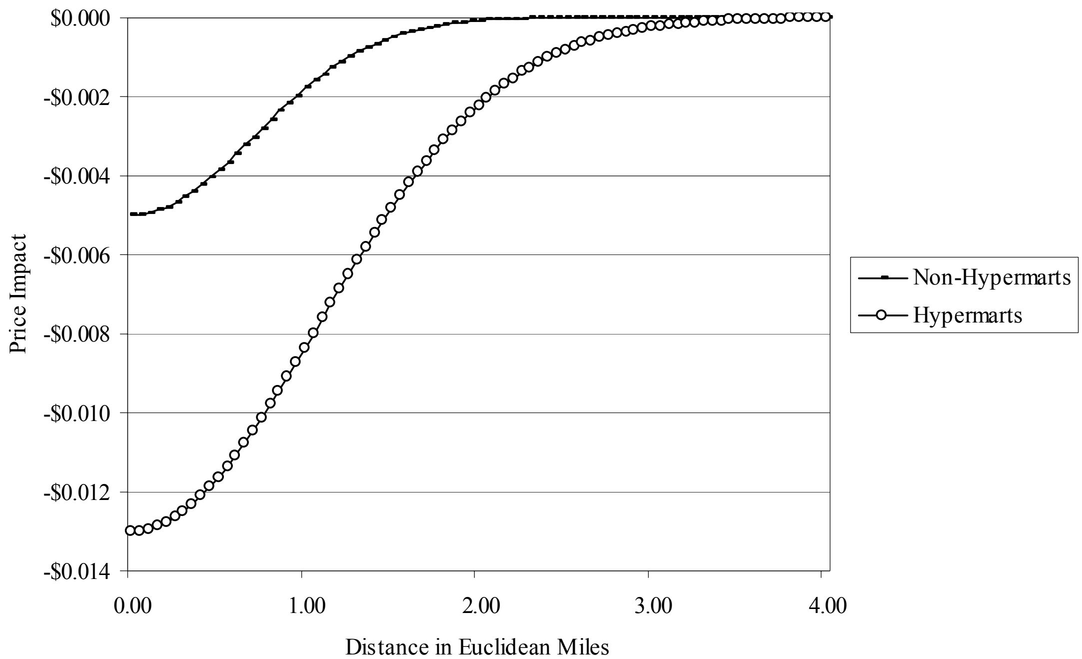


Table 4.7

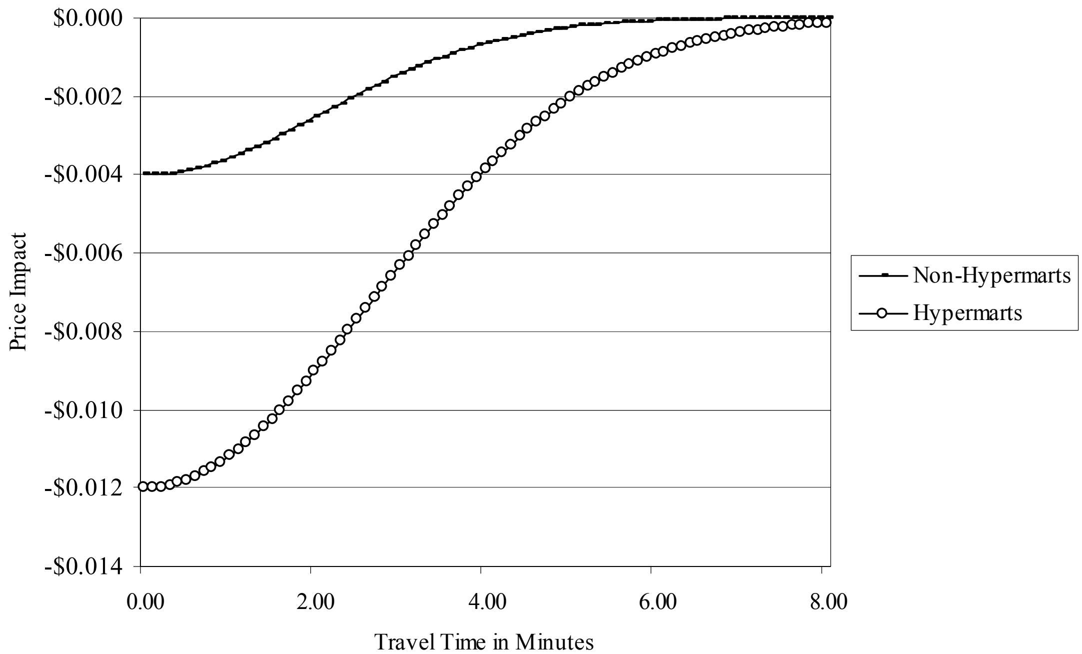
Results Using Travel Times

	Coefficient value	s.e.	p value	90% confidence interval low	high
Constant	1.992	0.010	0.000	1.976	2.008
Population density	1.242E-06	1.245E-06	0.319	-8.064E-07	3.289E-06
Traffic flow	0.000145	0.000089	0.104	-0.000002	0.000292
Hypermart	-0.028	0.012	0.024	-0.048	-0.008
Arco	-0.027	0.009	0.002	-0.042	-0.013
Chevron	0.071	0.007	0.000	0.060	0.083
Conoco	-0.012	0.009	0.189	-0.026	0.003
Citgo	0.034	0.011	0.002	0.015	0.052
Diamond Shamrock	-0.023	0.008	0.002	-0.036	-0.011
Exxon	0.045	0.010	0.000	0.028	0.062
Mobil	0.041	0.008	0.000	0.028	0.055
Shell	0.061	0.009	0.000	0.045	0.076
76	0.022	0.012	0.056	0.003	0.042
Texaco	0.059	0.013	0.000	0.038	0.080
Convenience store	-0.004	0.008	0.553	-0.017	0.008
Franchise food outlet	0.014	0.007	0.047	0.002	0.026
Car wash	0.003	0.008	0.711	-0.011	0.017
Repair shop	0.013	0.007	0.078	0.001	0.025
α hypermarts (α_h)	2.654	1.523	0.081	0.149	5.159
λ hypermarts (λ_h)	-0.012	0.008	0.133	-0.025	0.001
α non-hypermarts (α_n)	2.091	0.570	0.000	1.153	3.028
λ non-hypermarts (λ_n)	-0.004	0.002	0.115	-0.008	0.000
Log of HI of brand counts (μ)	-0.027	0.014	0.050	-0.050	-0.004

Travel times are measured in whole minutes with no times less than one minute.

Figure 4.3

Estimated Price Impact of Hypermart and Non-Hypermart Gas Stations Based on Travel Time from Station of Interest



C.2: Results of 1st Adapted Model

The 1st adapted model separates non-hypermarts into unbranded and branded stations and utilized separate counts for these categories.

Table 4.8

Results of 1st Adapted Model Using Road Distances

	Coefficient value	s.e.	p value	90% confidence interval low	90% confidence interval high
Constant	1.995	0.009	0.000	1.980	2.010
Population density	2.098E-06	1.478E-06	0.156	-3.318E-07	4.529E-06
Traffic flow	0.000147	0.000087	0.091	0.000004	0.000291
Hypermart	-0.038	0.013	0.003	-0.060	-0.017
Arco	-0.039	0.011	0.000	-0.057	-0.022
Chevron	0.062	0.009	0.000	0.047	0.077
Conoco	-0.021	0.010	0.039	-0.037	-0.004
Citgo	0.032	0.012	0.007	0.012	0.051
Diamond Shamrock	-0.033	0.009	0.001	-0.049	-0.017
Exxon	0.037	0.011	0.001	0.018	0.056
Mobil	0.034	0.009	0.000	0.018	0.049
Shell	0.052	0.010	0.000	0.035	0.069
76	0.015	0.013	0.239	-0.006	0.036
Texaco	0.054	0.013	0.000	0.032	0.076
Convenience store	-0.007	0.007	0.377	-0.019	0.006
Franchise food outlet	0.012	0.007	0.092	0.000	0.024
Car wash	0.001	0.009	0.887	-0.013	0.015
Repair shop	0.012	0.007	0.090	0.000	0.024
α hypermarts (α_h)	1.374	0.615	0.026	0.362	2.386
λ hypermarts (λ_h)	-0.021	0.009	0.021	-0.035	-0.006
α unbranded stations(α_{ub})	1.121	0.219	0.000	0.761	1.480
λ unbranded stations (λ_{ub})	-0.002	0.002	0.291	-0.006	0.001
α branded stations (α_b)	0.361	0.234	0.123	-0.024	0.747
λ branded stations (λ_b)	-0.017	0.007	0.020	-0.028	-0.005
Log of HI of brand counts (μ)	-0.067	0.031	0.029	-0.118	-0.017

Road distances are measured in miles to the nearest foot.

C.3: Results of 2nd Adapted Model

The 2nd adapted model divides the unbranded category into three sub-categories: Circle K stations; Quik-Mart stations; and, Other stations.

Table 4.9

Results of 2nd Adapted Model Treating Other Stations as a Single Category and Using Road Distances

	Coefficient value	s.e.	p value	90% confidence interval low	90% confidence interval high
Constant	1.995	0.009	0.000	1.980	2.010
Population density	1.955E-06	1.375E-06	0.155	-3.075E-07	4.217E-06
Traffic flow	0.000121	0.000091	0.181	-0.000028	0.000270
Hypermart	-0.028	0.013	0.030	-0.048	-0.007
Arco	-0.031	0.009	0.000	-0.045	-0.016
Chevron	0.070	0.007	0.000	0.058	0.082
Conoco	-0.011	0.009	0.203	-0.026	0.003
Citgo	0.034	0.011	0.002	0.016	0.053
Diamond Shamrock	-0.026	0.008	0.001	-0.038	-0.013
Exxon	0.043	0.011	0.000	0.026	0.060
Mobil	0.040	0.008	0.000	0.027	0.054
Shell	0.059	0.009	0.000	0.043	0.074
76	0.019	0.012	0.117	-0.001	0.039
Texaco	0.059	0.013	0.000	0.038	0.080
Quik-Mart	-0.012	0.008	0.131	-0.025	0.001
Other	-0.003	0.007	0.645	-0.015	0.009
Convenience store	-0.007	0.008	0.341	-0.020	0.005
Franchise food outlet	0.016	0.007	0.029	0.004	0.028
Car wash	0.006	0.008	0.444	-0.007	0.020
Repair shop	0.014	0.007	0.057	0.002	0.026
α hypermarts (α_h)	1.496	0.679	0.028	0.378	2.613
λ hypermarts (λ_h)	-0.013	0.007	0.093	-0.025	-0.000
α non-hypermarts (α_n)	0.656	0.125	0.000	0.451	0.860
λ non-hypermarts (λ_n)	-0.009	0.004	0.014	-0.016	-0.003
Log of HI of brand counts (μ)	-0.035	0.017	0.047	-0.063	-0.006

Road distances are measured in miles to the nearest foot.

Table 4.10

Results of 2nd Adapted Model Treating Other Stations as Separate Categories and Using Road Distances

	Coefficient value	s.e.	p value	90% confidence interval low	90% confidence interval high
Constant	1.995	0.009	0.000	1.980	2.010
Population density	1.833E-06	1.369E-06	0.181	-4.190E-07	4.085E-06
Traffic flow	0.000120	0.000090	0.182	-0.000028	0.000269
Hypermart	-0.027	0.013	0.033	-0.048	-0.006
Arco	-0.031	0.009	0.000	-0.045	-0.017
Chevron	0.070	0.007	0.000	0.058	0.081
Conoco	-0.011	0.009	0.201	-0.026	0.003
Citgo	0.034	0.011	0.002	0.016	0.053
Diamond Shamrock	-0.025	0.008	0.001	-0.038	-0.013
Exxon	0.043	0.011	0.000	0.026	0.060
Mobil	0.040	0.008	0.000	0.027	0.054
Shell	0.059	0.009	0.000	0.043	0.074
76	0.019	0.012	0.117	-0.001	0.039
Texaco	0.059	0.013	0.000	0.038	0.080
Quik-Mart	-0.012	0.008	0.128	-0.025	0.001
Other	-0.004	0.007	0.546	-0.017	0.008
Convenience store	-0.007	0.008	0.339	-0.020	0.005
Franchise food outlet	0.016	0.007	0.027	0.004	0.028
Car wash	0.007	0.008	0.413	-0.007	0.021
Repair shop	0.013	0.007	0.067	0.001	0.026
α hypermarts (α_h)	1.526	0.683	0.025	0.402	2.649
λ hypermarts (λ_h)	-0.012	0.007	0.101	-0.024	0.000
α non-hypermarts (α_n)	0.641	0.120	0.000	0.444	0.837
λ non-hypermarts (λ_n)	-0.010	0.004	0.012	-0.016	-0.003
Log of HI of brand counts (μ)	-0.037	0.018	0.038	-0.066	-0.008

Road distances are measured in miles to the nearest foot.

C.4: Results Using Alternative Weighting Factors

Table 4.11

Results Using $w_{ij} = e^{-\left(\frac{d_{ij}}{\alpha}\right)}$ and Road Distances

	Coefficient value	s.e.	p value	90% confidence interval low	90% confidence interval high
Constant	1.994	0.009	0.000	1.979	2.009
Population density	2.732E-06	1.494E-06	0.067	2.743E-07	5.190E-06
Traffic flow	0.000140	0.000090	0.123	-0.000009	0.000288
Hypermart	-0.030	0.013	0.017	-0.051	-0.009
Arco	-0.031	0.009	0.000	-0.046	-0.017
Chevron	0.070	0.007	0.000	0.058	0.082
Conoco	-0.013	0.009	0.153	-0.027	0.002
Citgo	0.034	0.011	0.003	0.015	0.052
Diamond Shamrock	-0.026	0.008	0.001	-0.039	-0.013
Exxon	0.042	0.011	0.000	0.025	0.060
Mobil	0.040	0.008	0.000	0.026	0.053
Shell	0.059	0.009	0.000	0.044	0.075
76	0.019	0.012	0.116	-0.001	0.039
Texaco	0.059	0.013	0.000	0.037	0.080
Convenience store	-0.006	0.007	0.424	-0.018	0.006
Franchise food outlet	0.014	0.007	0.055	0.002	0.025
Car wash	0.005	0.008	0.556	-0.009	0.019
Repair shop	0.013	0.007	0.074	0.001	0.025
α hypermarts (α_h)	1.057	0.806	0.190	-0.269	2.384
λ hypermarts (λ_h)	-0.025	0.016	0.127	-0.051	0.002
α non-hypermarts (α_n)	0.655	0.172	0.000	0.372	0.937
λ non-hypermarts (λ_n)	-0.010	0.005	0.040	-0.018	-0.002
Log of HI of brand counts (μ)	-0.033	0.018	0.060	-0.062	-0.004

Road distances are measured in miles to the nearest foot.

Table 4.12

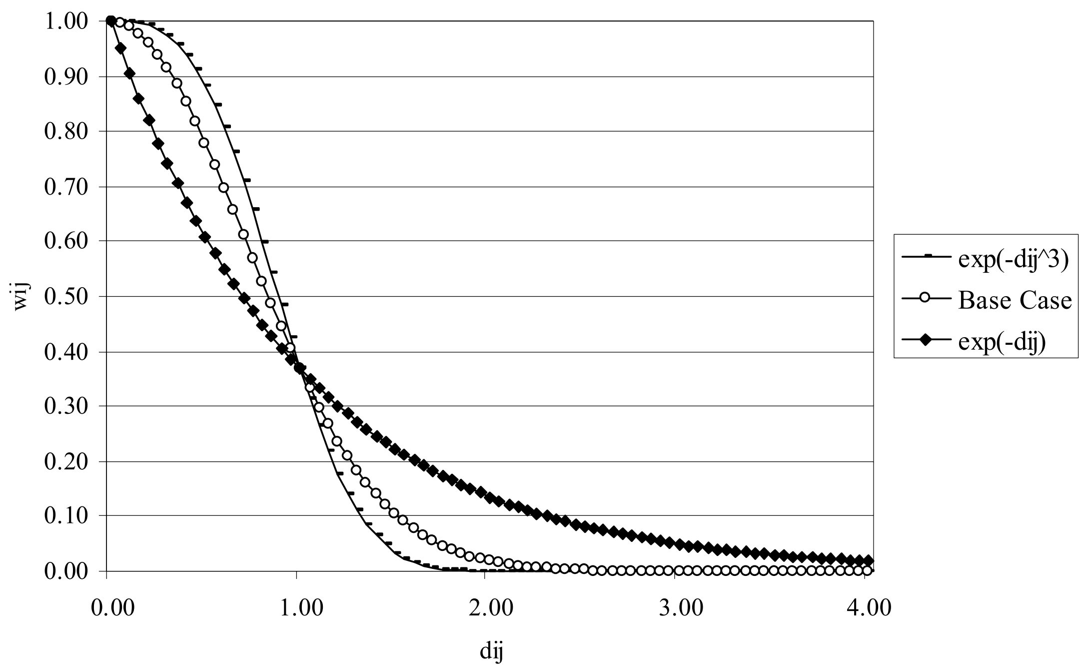
Results Using $w_{ij} = e^{-\left(\frac{d_{ij}}{\alpha}\right)^{3}}$ and Road Distances

	Coefficient value	s.e.	p value	90% confidence interval low	90% confidence interval high
Constant	1.993	0.009	0.000	1.978	2.008
Population density	2.857E-06	1.451E-06	0.049	4.698E-07	5.243E-06
Traffic flow	0.000160	0.000089	0.072	0.000014	0.000306
Hypermart	-0.030	0.012	0.013	-0.050	-0.010
Arco	-0.027	0.009	0.001	-0.041	-0.013
Chevron	0.072	0.007	0.000	0.060	0.083
Conoco	-0.011	0.009	0.204	-0.025	0.003
Citgo	0.035	0.011	0.002	0.016	0.053
Diamond Shamrock	-0.024	0.008	0.001	-0.037	-0.012
Exxon	0.045	0.010	0.000	0.028	0.062
Mobil	0.042	0.008	0.000	0.029	0.056
Shell	0.061	0.009	0.000	0.046	0.076
76	0.021	0.012	0.065	0.002	0.040
Texaco	0.061	0.013	0.000	0.040	0.082
Convenience store	-0.007	0.008	0.372	-0.019	0.006
Franchise food outlet	0.013	0.007	0.061	0.002	0.025
Car wash	0.003	0.008	0.739	-0.011	0.017
Repair shop	0.014	0.007	0.058	0.002	0.026
α hypermarts (α_h)	2.380	0.796	0.003	1.071	3.689
λ hypermarts (λ_h)	-0.011	0.005	0.028	-0.020	-0.003
α non-hypermarts (α_n)	1.488	0.323	0.000	0.957	2.018
λ non-hypermarts (λ_n)	-0.004	0.002	0.042	-0.006	-0.001
Log of HI of brand counts (μ)	-0.022	0.012	0.067	-0.042	-0.002

Road distances are measured in miles to the nearest foot.

Figure 4.4

Comparison of Different Forms of the Weighting Factor



For ease of comparison, the base case weighting factor is shown with $\alpha = 1/\sqrt{2}$ while for the other two cases $\alpha = 1$.

C.5: Results of Distance Ring Model

Table 4.13

Results Using Distance Ring Model and Road Distances

	Coefficient value	s.e.	p value	90% confidence interval low	high
Constant	1.995	0.009	0.000	1.980	2.010
Population density	2.304E-06	1.415E-06	0.103	-2.288E-08	4.632E-06
Traffic flow	0.000165	0.000086	0.055	0.000024	0.000307
Hypermart	-0.026	0.012	0.029	-0.046	-0.007
Arco	-0.024	0.008	0.005	-0.038	-0.010
Chevron	0.074	0.007	0.000	0.063	0.085
Conoco	-0.008	0.009	0.347	-0.023	0.006
Citgo	0.036	0.011	0.001	0.018	0.054
Diamond Shamrock	-0.023	0.008	0.002	-0.035	-0.010
Exxon	0.044	0.010	0.000	0.027	0.061
Mobil	0.046	0.008	0.000	0.033	0.059
Shell	0.063	0.009	0.000	0.048	0.077
76	0.026	0.011	0.024	0.007	0.044
Texaco	0.067	0.013	0.000	0.047	0.088
Convenience store	-0.006	0.007	0.397	-0.019	0.006
Franchise food outlet	0.013	0.007	0.057	0.002	0.025
Car wash	0.005	0.008	0.577	-0.009	0.019
Repair shop	0.012	0.007	0.092	0.000	0.024
# hypermarts 0 to 1 mile	-0.005	0.006	0.392	-0.015	0.005
# hypermarts 1 to 2 miles	-0.007	0.004	0.074	-0.014	-0.001
# hypermarts 2 to 3 miles	-0.006	0.003	0.048	-0.011	-0.001
# non-hypermarts 0 to 1 mile	-0.003	0.001	0.020	-0.006	-0.001
# non-hypermarts 1 to 2 miles	-0.001	0.001	0.081	-0.002	-0.000
# non- hypermarts 2 to 3 miles	0.001	0.001	0.179	-0.000	0.002

Road distances are measured in miles to the nearest foot.

C.6: Results of Autoregressive Spatial Model

Table 4.14

Results of Autoregressive Spatial Model Using Road Distances

	Coefficient value	s.e.	p value	90% confidence interval low	high
Constant	1.994	0.009	0.000	1.979	2.008
Population density	2.819E-06	1.327E-06	0.034	6.373E-07	5.002E-06
Traffic flow	0.000154	0.000088	0.080	0.000009	0.000299
Hypermart	-0.030	0.012	0.014	-0.050	-0.010
Arco	-0.028	0.009	0.001	-0.042	-0.014
Chevron	0.071	0.007	0.000	0.060	0.083
Conoco	-0.011	0.009	0.197	-0.025	0.003
Citgo	0.035	0.011	0.002	0.016	0.053
Diamond Shamrock	-0.025	0.008	0.001	-0.037	-0.012
Exxon	0.044	0.010	0.000	0.027	0.061
Mobil	0.041	0.008	0.000	0.028	0.055
Shell	0.060	0.009	0.000	0.045	0.075
76	0.020	0.012	0.078	0.001	0.040
Texaco	0.060	0.013	0.000	0.039	0.082
Convenience store	-0.007	0.008	0.376	-0.019	0.006
Franchise food outlet	0.013	0.007	0.060	0.002	0.025
Car wash	0.004	0.008	0.640	-0.010	0.018
Repair shop	0.014	0.007	0.052	0.002	0.026
λ hypermarts (λ_h)	-0.014	0.005	0.011	-0.023	-0.005
λ non-hypermarts (λ_n)	-0.005	0.002	0.001	-0.007	-0.002
Log of HI of brand counts (μ)	-0.024	0.013	0.071	-0.045	-0.002
ρ	0.00071				

Road distances are measured in miles to the nearest foot.

$\alpha_u = 0.33$ was used since this value minimized the sum of squared residuals

Table 4.15

Results of Autoregressive Spatial Model Using Euclidean Distances

	Coefficient value	s.e.	p value	90% confidence interval low	high
Constant	1.994	0.009	0.000	1.979	2.009
Population density	2.914E-06	1.329E-06	0.028	7.285E-07	5.099E-06
Traffic flow	0.000173	0.000088	0.050	0.000028	0.000318
Hypermart	-0.026	0.012	0.033	-0.045	-0.006
Arco	-0.029	0.009	0.001	-0.043	-0.015
Chevron	0.072	0.007	0.000	0.060	0.083
Conoco	-0.011	0.009	0.200	-0.025	0.003
Citgo	0.034	0.011	0.003	0.015	0.052
Diamond Shamrock	-0.025	0.008	0.001	-0.038	-0.013
Exxon	0.044	0.010	0.000	0.028	0.061
Mobil	0.040	0.008	0.000	0.026	0.053
Shell	0.060	0.009	0.000	0.045	0.075
76	0.021	0.012	0.076	0.001	0.040
Texaco	0.059	0.013	0.000	0.038	0.080
Convenience store	-0.005	0.007	0.480	-0.018	0.007
Franchise food outlet	0.013	0.007	0.066	0.001	0.025
Car wash	0.004	0.008	0.640	-0.010	0.018
Repair shop	0.014	0.007	0.049	0.002	0.026
λ hypermarts (λ_h)	-0.013	0.005	0.016	-0.021	-0.004
λ non-hypermarts (λ_n)	-0.005	0.001	0.001	-0.008	-0.003
Log of HI of brand counts (μ)	-0.021	0.014	0.125	-0.044	0.002
ρ	0.00582				

Euclidean distances are measured in miles to the nearest foot.

α_u = 0.34 was used since this value minimized the sum of squared residuals.

Table 4.16

Results of Autoregressive Spatial Model Using Travel Times

	Coefficient value	s.e.	p value	90% confidence interval low	high
Constant	1.992	0.009	0.000	1.976	2.007
Population density	1.242E-06	1.176E-06	0.291	-6.925E-07	3.176E-06
Traffic flow	0.000145	0.000087	0.094	0.000003	0.000287
Hypermart	-0.028	0.012	0.024	-0.048	-0.008
Arco	-0.027	0.009	0.001	-0.041	-0.013
Chevron	0.071	0.007	0.000	0.060	0.083
Conoco	-0.012	0.009	0.186	-0.026	0.003
Citgo	0.034	0.011	0.002	0.015	0.052
Diamond Shamrock	-0.023	0.008	0.002	-0.036	-0.011
Exxon	0.045	0.010	0.000	0.028	0.062
Mobil	0.041	0.008	0.000	0.028	0.055
Shell	0.061	0.009	0.000	0.045	0.076
76	0.022	0.012	0.055	0.003	0.042
Texaco	0.059	0.013	0.000	0.038	0.080
Convenience store	-0.004	0.008	0.552	-0.017	0.008
Franchise food outlet	0.014	0.007	0.047	0.002	0.026
Car wash	0.003	0.008	0.709	-0.011	0.017
Repair shop	0.013	0.007	0.077	0.001	0.025
λ hypermarts (λ_h)	-0.012	0.006	0.036	-0.021	-0.003
λ non-hypermarts (λ_n)	-0.004	0.001	0.010	-0.006	-0.001
Log of HI of brand counts (μ)	-0.027	0.014	0.048	-0.050	-0.005
ρ	3.693E-06				

Travel times are measured in whole minutes with no times less than one minute.

$\alpha_u = 0.21$ was used since this value minimized the sum of squared residuals.

C.7: Station Ownership Analysis

Table 4.17

Analysis of Gas Station Ownership Groups

Name of Ownership Group	# Stations
Circle K Stores Inc	83
Loma Catalina Co	16
Diamond Shamrock Arizona Inc	14
Quik-Mart Stores Inc	14
Giant Industries Arizona Inc	10
BP West Coast Products LLC	8
Shell Oil Products	8
AZ Portfolio Properties Group LLC	7
7-Eleven Inc	6
Reays Ranch Investors LLC	6
ConocoPhillips	5
Cox Investment Group LLC	5
C and T Oil Company	4
Chevron Products Co	4
Frys Food Stores of America Inc	3
Capin Enterprises Inc	2
Costco Wholesale	2
No ownership group	38
Total	235

The 3rd adapted model includes an additional variable; the Herfindahl index of ownership group counts.

Table 4.18

Results of 3rd Adapted Model Using Road Distances

	Coefficient value	s.e.	p value	90% confidence interval Low	high
Constant	1.993	0.010	0.000	1.977	2.009
Population density	2.803E-06	1.555E-06	0.071	2.464E-07	5.360E-06
Traffic flow	0.000152	0.000091	0.095	0.000002	0.000301
Hypermart	-0.030	0.012	0.013	-0.050	-0.010
Arco	-0.028	0.009	0.001	-0.043	-0.014
Chevron	0.071	0.007	0.000	0.060	0.083
Conoco	-0.011	0.009	0.209	-0.025	0.003
Citgo	0.035	0.011	0.002	0.016	0.053
Diamond Shamrock	-0.025	0.008	0.001	-0.037	-0.012
Exxon	0.045	0.010	0.000	0.027	0.062
Mobil	0.042	0.008	0.000	0.028	0.055
Shell	0.061	0.009	0.000	0.046	0.076
76	0.020	0.012	0.079	0.001	0.040
Texaco	0.061	0.013	0.000	0.039	0.082
Convenience store	-0.007	0.008	0.368	-0.019	0.006
Franchise food outlet	0.013	0.007	0.063	0.002	0.025
Car wash	0.004	0.009	0.632	-0.010	0.018
Repair shop	0.014	0.007	0.059	0.002	0.026
α hypermarts (α_h)	1.458	0.644	0.024	0.398	2.518
λ hypermarts (λ_h)	-0.014	0.007	0.050	-0.025	-0.002
α non-hypermarts (α_n)	0.872	0.216	0.000	0.517	1.226
λ non-hypermarts (λ_n)	-0.005	0.003	0.049	-0.009	-0.001
Log of HI of brand counts (μ)	-0.020	0.019	0.288	-0.051	0.011
α ownership group (α_{og})	1.000	2.032	0.623	-2.342	4.342
Log of HI of ownership group counts	-0.005	0.020	0.786	-0.038	0.027

Road distances are measured in miles to the nearest foot.

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