DO RACIALLY IDENTIFYING NAMES MATTER IN COMPETITIVE MARKETS? EVIDENCE FROM A FIELD EXPERIMENT

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Abstract

We conduct a field experiment in order to identify and quantify racial discrimination in a competitive market. We run a series of auctions, using eBay, and compare the final prices of identical products sold by sellers with distinctively black names to those sellers with distinctively white names. In a market for a race neutral product, sellers with distinctively black names initially receive significantly lower prices (7 percent) than those with distinctively white names. However, this effect becomes insignificant when sellers have accumulated a credible reputation through eBay's feedback system, which suggests the effect is due to statistical discrimination. Alternatively, in a market for distinctly black products, we find that sellers with distinctively black names receive significantly higher prices (13 percent) than those with distinctively white names. This effect appears to be due to taste-based discrimination, as the price differences persist with accumulated feedback.

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1. Introduction

Discrimination is a controversial and important topic. The investigation of such a sensitive issue, for which little reliable data exist, is notoriously difficult to quantify and test empirically. An experimental framework is particularly helpful in detecting discrimination given theoretical predictions that in a competitive market “the least discriminatory firms survive.” (Arrow 1973) Identifying discrimination requires creating a realistic decision-making environment without sacrificing the control of the experiment. Survey methods are problematic, because participants may not feel comfortable revealing their true preferences and may not have any incentive to do so. Likewise, to the extent that discriminatory factors are present subconsciously or implicitly, an experimental design that brings the issue into conscious thought is not able to capture the true effect. Using racially distinct names, we study discrimination by selling goods in a competitive market in which all factors are held constant, except for the names of the sellers.

Over the past 30-40 years, the names given to white and black children have diverged substantially (Fryer and Levitt 2004). Names such as DeShawn, Jamal, and Tyrone were given to male black children at high rates relative to white children, while names such as Jake, Conner, and Dustin rank atop the list of the "whitest" names for males (Levitt and Dubner 2005). Previous work on the consequences of distinctively black names has produced mixed results. Fryer and Levitt (2004) find little empirical evidence linking distinctively black names to worse adult outcomes (such as income, education, or marital status), while Bertand and Mullainathan (2004) find that job applicants with distinctively black names receive far fewer callbacks than those with distinctively black names.

We extend the literature on racial discrimination by conducting a controlled experiment in a field setting to test our hypothesis that racially identifying names lead to different prices in competitive markets. In particular, we conduct a series of auctions using eBay, and compare the final prices of identical products sold by sellers with distinctively black names relative to those sellers who have distinctively white names. Our approach has a number of advantages over previous studies. First, our single-blind design elicits true preferences from our subjects, who are real buyers shopping on eBay, not recruits in a laboratory, and cannot act in order to appease the experimenter. Winning an auction is costly – a bidder who wins is obligated to pay the final price, and is then mailed the product(s) in question. Second, eBay's feedback system encourages reputation building, which in certain cases allows us to distinguish between taste-based and statistical discrimination. Third, our experiment rules out differences in bargaining power, which is cited by List (2004) as a reason for finding evidence of discrimination. The products are sold in an online auction, in which bargaining is not possible. Finally, the markets studied are relatively free of government regulation, compared to housing and labor markets, which have been the focus of most research on discrimination. This allows us to test for discrimination with subjects who are not required to consider hundreds of laws in place to reduce discrimination.

A potential way for statistical discrimination to arise is if a buyer believes that a seller with a distinctively white name is more (or less) likely to deliver the product as advertised relative to a seller with a distinctively black name. Both eBay and PayPal[1] have policies providing fraud protections to buyers, and there is a reputation mechanism providing information on the satisfaction of other buyers who participated in previous transactions with the seller. As our sellers earn more credible reputations throughout the experiment, via eBay's feedback system, the information asymmetry becomes less of an issue.

[1] PayPal operates a financial service that processes payments for their clients for sales brokered across the Internet. They are owned by eBay Inc. and their service is the preferred payment method for eBay.com.

In our auctions we sell pairs of identical products in two distinct markets. In the first, a race-neutral market, we sell fishing lures. In the second, we sell distinctively black toys.[2] Each auction is paired such that a seller with distinctively white name and a seller with a distinctively black name are selling identical products at the same time. Comparing the prices received, we show that new sellers with distinctively black initially names receive significantly lower prices in the race neutral market. This effect disappears as the sellers accumulate feedback, and the information asymmetry between buyer and seller is reduced – leaving us to conclude that the type of discrimination observed is likely statistical. Preliminary results from the distinctively black market show that sellers with distinctively black names receive significantly higher prices than sellers with distinctively white names. This effect does not decrease with information and feedback. This finding marks the first empirical evidence of the benefit to having a distinctive name in the minority.[3]

[2] We are currently gathering data on distinctively white products as well. There is currently not enough data to draw inference from..

[3] See Fryer and Levitt (2004) for rational choice theories of parents' choice in naming their child.

2. Background

2.1. Statistical Versus Taste-Based Discrimination

Standard economic theory makes the simplifying assumption that the physical characteristics (e.g., race, gender, age) of agents in a market are irrelevant. However, in many market situations, their identity and characteristics are thought to be important factors (Akerlof and Kranton 2000). There are two primary economic models of discrimination: one based on tastes (Becker 1957) and the other based on statistical discrimination arising from incomplete information (Arrow 1973; Phelps 1972). In the taste-based model, economic agents pay a premium (either in terms of lost revenue or higher prices) to avoid trading with those from a particular class of people. By contrast, discriminatory models emphasizing incomplete information rely on making inference about another based on their characteristics (e.g., race or gender). While the taste-based model suggests that discrimination arises due to preferences, models based on statistical discrimination assume economic agents have no such animosity. Nevertheless, statistical "discrimination" still results in people being treated differently because of their characteristics.

Statistical discrimination can arise in any market affected by information asymmetry. If market participants believe that their trading partners' characteristics suggest information otherwise unavailable, use of that information can result in statistical discrimination. That is, physical characteristics may be used as a signal through which unknown information can be inferred. In an eBay auction, for example, the seller has better information than potential buyers on (*i)* the quality of the good being sold and (*ii)* the probability that it will be shipped. If a buyer were to make assumptions about the quality of the good in question based on the seller's race, a discriminatory finding would be statistical rather than taste based.

The difference between taste-based and statistical discrimination is an important one. If discrimination is rooted in differences in information, and not prejudice, we are immediately presented with the opportunity to minimize discrimination through market mechanisms that reduce information asymmetry.

The auction framework has been celebrated as a mechanism which elicits buyers' true preferences and converges to efficient outcomes. (McAfee and McMillan 1987) In order to actually observe discrimination within this framework a discriminatory bidder must (*i*) view the username of the our seller (though there is no expectation of useful or identifying information in a username) (*ii*) perceive the name as indicating the given race (*iii*) bid on the item for sale, (*iv*) not be outbid by other consumers or arbitrages taking advantage of the price differential.

2.2. Identifying Racial Discrimination

Attempts to examine racial discrimination, in general, have used regression analysis[4] and field experiments.[5] An obvious issue arising in the regression framework is the influence of omitted variables. The regression approach traditionally uses an economic outcome as the dependent variable (usually a price) and controls for observable characteristics. The key explanatory variable of interest is typically membership in a minority group (e.g., Hispanic or black). However, in this framework, unobserved differences between majority and minority groups could lead to differences in the outcome of interest that are not attributable to

[4] Altonji and Blank (1999) present a comprehensive review of regression studies focusing on the labor market. For the most part, these studies find lower wages or job opportunities for minorities. Regression studies, however, have come under serious criticism. The choice of independent variables, and what data to use for these studies, have led to different results (Riach and Rich 2002).

[5] In order to side-step these problems inherent in regression studies, many researchers have turned to so-called audit studies. Riach and Rich (2002) present an extensive review of audit studies that examine discrimination in product and labor markets. Audit studies attempt a controlled field experiment by sending two people, who are of different race or gender, into the marketplace. These studies typically find preferential treatment for whites relative to blacks.

discrimination. In the audit framework, the main concern is ensuring that the auditors do not differ in either observed or unobserved ways. To circumvent potential issues with unobservables, auditors are trained to use the same bargaining strategy. Despite this training, the audit approach has been criticized because the auditors could differ in unobserved ways, perhaps in terms of perceived lower reservation prices (Heckman 1998).

This problem has recently been averted by studies that, instead of sending people to apply for a job, send resumes that differ only by the racial distinctiveness of the applicants' names. Bertrand and Mullainathan (2004) find that those applicants with white names receive 50 percent more interviews. They also show that this discrimination holds across socio-economic class and the quality of skill-sets presented on the resumés.

Similarly, Fryer and Levitt (2004) use a natural-experiment approach to racial discrimination by studying birth records from the California Department of Health Services to determine if having a distinctively black name leads to negative outcomes later in life. They show that having a distinctly black name has a small effect on the type of neighborhood in which a subject lives, and a positive but small effect on the likelihood they are single mothers. For other outcomes, including education and income, having a unique and culturally distinctive name is shown to have no effect.

List (2004) makes a number of important contributions to the study of discrimination with a novel field experiment in a baseball-card market: (*i*) he examines a market which has a simple structure (relative to the more complex housing or labor markets that are the subject of most studies of discrimination) by recruiting subjects of different races, genders, and ages to buy and sell cards, (*ii*) his experiment provides a potential way to separate the effects of taste-based and statistical discrimination, and (*iii*) he studies both the buyer and seller sides of the market.[6] List's study (2004) conducts auctions[7] and bargaining markets but also runs supplemental experiments to test dealer's perceptions and subjects' preference for discrimination using dictator games.

The results from List's (2004) study show, first, that non-majority buyers (sellers) are quoted higher (lower) prices. List also shows that the difference in treatment of minorities is due to statistical discrimination and is not due to either taste-based discrimination or differences in bargaining.[8] In the market for trading cards race, gender, and age are used as a proxy for reservation values. Differences in prices earned by minority and majority members, then, are caused by the beliefs buyers (sellers) have about a seller's (buyers) reservation price, and not from prejudice. Lastly, the List study highlights that buyers discriminate against sellers more than the other way around.

2.3. eBay

We sell our goods on eBay, and accept payment only through PayPal. Internet auctions, which match buyers and sellers from across the globe, are clearly characterized by significant information asymmetries.[9] (Akerlof 1970) Both eBay and PayPal (which is currently owned by eBay Inc.) have constructed profitable businesses only by helping their customers overcome these imperfections. By using eBay as our experimental platform, we not only have a novel way to test for discrimination but also a potential way to distinguish between statistical and taste-based discrimination.

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[6] Previous studies have been confined to studying discrimination of the buyers' side of the market.

[7] The auctions performed by List (2004) are different from those run in this study. List uses a sealed bid second price auction where the item being sold was awarded to a randomly selected bidder.

[8] While other studies (e.g. Ayres and Siegelman 1995; Goldberg 1996) have shown evidence of the difference between statistical and taste-based discrimination in their results, List (2004) explicitly tests for it.

[9] The FBI reports that there were 275,284 complaints filed for Internet crimes in 2008, 33% of which for non-payment/delivery and 26% of which were for auction fraud. (FBI 2008) These crimes represent an estimated total loss of 264.6 million dollars. (FBI 2008)

The only signal a buyer on eBay has about the quality of the good being sold is the seller's description of the good, the seller's feedback score, comments left by previous buyers, the seller's reported geographic location, a picture(s) of the item for sale, and, important for this study, the seller's username. The buyer must trust the description, believe the seller will ship the product, and expect the product to be in the stated quality upon receipt. Given our design, however, buyers have no reason to fear losing the money sent to a seller. If they do not receive the good they purchase, they only need to file a complaint with PayPal in order to have their money refunded. As a result, the cost of fraud is only that of calling to file a complaint, and the opportunity cost of the money paid until it is returned.[10]

Additionally, we attempt to reduce the effect of differences in information of our products' quality in selecting what products to sell. We sell products that are (*i*) brand new, (*ii*) the condition of the good is not of paramount importance, and (*iii*) come packaged in material that will keep the good relatively protected during shipping (which we advertise to buyers). If we sold collectible or fragile items over the Internet then the buyers would be very concerned with the quality of the item.

Finally, eBay's feedback system works to increase the information available between buyer and seller by publicizing their feedback scores and comments from previous trading partners each user has previously interacted with.[11] Upon completion of an eBay auction the buyer and seller have the opportunity to leave feedback for each other. Sellers receive -1 if the buyer is displeased with the service, a +1 if the buyer is happy with the transaction, or a 0 if the buyer is neutral. They can also leave comments describing the service received. While viewing items

[10] If the buyer uses a credit card with PayPal, and most do, the opportunity cost of their money is essentially zero.

[11] Bajari and Hortacsu (2004) review a number of papers on eBay's feedback mechanism and the effect it has on prices earned, showing that, in general, additional positive feedback increases the price earned and negative feedback reduces it..

available for sale, each seller’s feedback score (the sum of all individual scores), as well as the percentage of positive scores, and “star awards,” are shown on each item's description page. After receiving a certain number of positive feedback responses an eBay user receives a star award of a certain color that appears next to their name (e.g. yellow star for a feedback score of 10; blue for 50; and turquoise for 100). Further investigation into a user’s account shows a detailed listing of recent feedback, including the comments provided by previous buyers.

3. Experimental Design

We perform a series of auctions on eBay to test our hypothesis that racially identifying names have no effect on the price sellers receive in a competitive market. eBay is an ideal setting to examine this question because the markets are competitive and real buying decisions are being considered by individuals who have an interest in the product. We are able to control for numerous potential confounds by constructing a direct comparison of prices paid for identical products sold by sellers with racially identifying names. In this framework, there are real monetary consequences from bidding in an auction, and the buyers are largely anonymous. Buyers have little reason to hide their true preferences, as the cost of placing a bid in each auction is identical.

Over a period of 30 weeks we conduct 178 auctions of goods with retail values of five to seven dollars. In the market for a race neutral product we sell fishing lures. The various models of lures can be categorized as either "soft plastic worms" or "spinnerbaits." The fishing products were sold two at a time to minimize shipping costs. Identical color combinations were sold in each pair, in case buyers had preferences for certain colors. The product choices in the market for fishing lures were initially motivated by one author's experience selling fishing supplies on eBay. In the market for distinctively black products we sold various black dolls. The products sold, and their average auction prices, are shown in Table 1. All products were purchased at local retail chains, with the exception of the black "Dollhouse" figures, which were purchased online.

We conduct auctions using the standard eBay auction format with ascending English Auction rules with the addition of a computerized proxy bid system, so that bidders need not continuously monitor and bid on the auction.[12] Bidders enter their maximum willingness to pay, but the high

[12] See Lucking-Reiley *et al.* (2007) for further discussion of the proxy bidding system.

bid is only raised by the minimum bid over the second highest bid.[13] As such, the final selling price reveals the true willingness to pay of the bidder with the second highest value for the item. The willingness to pay for the winning bidders in our auctions cannot be determined.[14]

We use four different seller names in each market, which are selected from the list of distinctly black and distinctly white names provided by Levitt and Dubner (2005). The names chosen to represent our black sellers in the race neutral product market are DeShawn (first on the list) and Tyrone (eighth on the list), while the names chosen to represent our white sellers are Jake (first on the list) and Dustin (sixth on the list).[15] In the market for distinctively products, we sell using four completely separate accounts.[16] These were named Tyrone, Jake, and Dustin again, but Deshawn was replaced with Jamal (13th on the list).[17]

We schedule the auctions in each market so that a distinctly white name and a distinctly black name sell identical products at the same time. This provides prospective buyers, who may have a racial preference, the choice between two sellers. It is possible for a buyer to enter a bid in both auctions simultaneously.[18] There are also other sellers in the market with similar or identical products. However, the effect these had would be virtually the same for both of our sellers.

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[13] The minimum bid is a function of the current price. A buyer must bid in increments of $0.05 if the price is between $0.01 and $0.99; $0.25 if the price is between $1.00 and $4.99; or $0.50 if the price is between $5.00 and $24.99. None of our products sold for more than $25.

[14] This auction framework is a better mechanism than posted price markets for identifying discrimination. Posted price markets only convey whether buyers have a willingness to pay that equals or exceeds the price. If the price is below their maximum willingness-to-pay, they make the purchase. However, if the price is greater than their maximum willingness-to-pay, they do not make the purchase. For our purposes, this type of pricing would capture race differences only if the willingness-to-pay to a seller with a distinctively white name is greater than or equal to the price *and* the willingness–to-pay to a seller with a distinctively black name is less than the posted price at the same time.

[15] Since the names we use are as "usernames" and not actual names, we had to disregard any name that is a common last name, since these are less racially distinct. The actual seller names used in the race neugral market were *deshawn_#*, *tyrone_#*, *jake_#*, and *dustin_#*.

[16] The actual seller names used in the distinctively black market were *jamal_#*, *tyrone_#*, *jake_#*, and *dustin_#*.

[17] After some initial results, we felt that DeShawn may not be recognized as distinctively black as a username, as buyers might just focus on "Shawn."

[18] A total of 729 different people bid on our items. Only 79% bid on only one item. Out of 180 auctions there were 165 unique auction winners. There were five pairs of auctions where both items were won by the same buyer.

However, both of our sellers compete against these other sellers, and they should affect our sales identically. We have data about other products in the market as well.

We include a fact based description for the product in each auction to describe the product, its manufacturer, model, quality and appearance.[19] Each seller uses the same description each time the product is sold. Before conducting the auctions, we test a number of descriptions for significant differences by issuing a survey to undergraduate students. The details on testing descriptions are in The Appendix. With these results we ensure our auction descriptions are visibly different between sellers, but not in a way that will affect the price earned.

Within a pair, each auction runs for five days and ends two days apart.[20,21] Thus, auctions for an identical product, under two names that differ by race, are running simultaneously from Sunday afternoon until Wednesday afternoon.[22] We also alternate the order of the auctions so that each seller sells each good ending first and second. This rotation, which we refer to as a cycle, is illustrated in Table 2.

We start each seller name as a new account so that each seller begins identical except for the username. As the sellers participate in more auctions their ratings increase in accordance with buyers' feedback as per eBay's rules. Since we coordinate the shipment of the products there is no reason to expect the feedback for each seller to differ. However, buyers are not required to rate a seller and slight differences emerge that are beyond our control. As a seller's feedback

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[19] An example of an auction description used can be seen in Figure 1.

[20] Lucking-Reiley *et al.* (2007) finds that products tend to be sold at higher prices on Mondays and volume is higher on Saturday and Sundays.

[21] The auctions in the first cycle of race-neutral products were scheduled to end on Wednesdays and Fridays. This was changed after finding that there was a significant difference in price from which day the auction ended on. There is no such effect when ending on Tuesdays and Thursdays. Whether an auction finishes first is controlled for in regressions, discussed below.

[22] While it may seem an unnecessary complication to run auctions at different times, in an initial pilot study we conducted a set of auctions which ended on the same day within a few hours of each other. After several weeks one buyer expressed some suspicion that our seller accounts were the same, and accused us of illegally bidding on our own products. We discontinued this setup because we could not fully trust the data.

score grows it provides buyers with more information, thus reducing the information asymmetry that can lead to statistical discrimination. By using the same user accounts through three different cycles of our experiment, we have the opportunity to see how the effect of discrimination changes over time as sellers acquire feedback.

Free shipping is offered on all products because shipping costs can vary by the location of the buyer. We must control for potential differences in costs to the greatest extent possible. We ship out all products sold via USPS first class, and only sell to buyers in the continental United States. All of this information is shown in each auction's description page. All of our sellers list "Southeastern USA" as their location instead of something more specific.[23]

All auctions begin with an initial price of $0.01, and have no minimum bid or reserve price set.[24] Furthermore, to keep buyers' information set as controlled as possible, communication from potential bidders is handled as uniformly as possible.[25]

We conduct a series of auctions over three eight week cycles, for both the market for race neutral products and distinctly black products, starting in February 2009, which rotates all of the possible combinations of black-white name pairings, and the order in which the auction finishes, for each product.

[23] Previous studies have shown that buyers are sensitive to differences in shipping costs (Hossain and Morgan, 2006), especially as they vary across the distance from buyer and seller (Hortacsu *et al.*, 2009).

[24] Minimum bids and reserve prices have been shown to have varying and largely adverse effects (Lucking-Reiley *et al*. 2007; Katkar and Reiley 2005; Bajari and Hortacsu 2003).

[25] The most common question was whether we would accept an alternate form of payment. Each time the questioner is told that we would only accept payment through PayPal (which is also listed in each auction description).

4. Results

4.1. Market for a Race Neutral Product

In the race neutral product market we run 96 auctions over 24 weeks. Our raw results can be seen in Figure 2 Figure 3, which show the final auction prices. Figure 1 shows one type of lures ("spinnerbait") while Figure 2 shows another ("soft plastic worms").

If the names of our sellers are, in fact, irrelevant then the difference between the prices in our paired auctions should not be different from zero. Table 3 shows the mean values for the difference in prices between paired auctions, along with t-tests, sign tests of equality of matched pairs, and Wilcoxon matched pairs signed-rank tests for the difference in prices.[26] Those sellers with white names (Jake and Dustin) earn, per sale on average, an additional \$0.75 over the sellers with black names (Tyrone and Deshawn) in the first 8 week cycle, which is significant at the five percent level. This difference drops to \$0.34 by the end of the second cycle, and then to \$0.17 when the experiment is complete. The middle panel of Table 3 shows the same numbers but for each cycle separately. This shows that the significant difference in price is driven by the first cycle. The final rows show the same tests but separated by product.

Table 4**Error! Reference source not found.** shows the revenue earned in this market, by race. White-named sellers earned \$275.64, while black-named sellers earned \$263.65. This table also shows what Becker (1957) calls the "Market Discrimination Coefficient," (MDC).[27]This data shows that white-named sellers earned, on average, almost five percent more than sellers with distinctively black names, in this market.

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[26] Specifically, the price difference is calculated for each auction by subtracting the price earned by the seller with a distinctively black name from the price earned by the seller with the distinctively white name.

[27] Market Discrimination Coefficient is calculated according to: $MDC = (\pi_W - \pi_B)/\pi_B$, where π_B and π_W are the revenue for black and white sellers, respectively.

In order to further investigate our results, we estimate the final price of our auctions according to Equation (1).[28] *Black Name* is an indicator for if the seller was named either Tyrone or Deshawn[29]. *Endfirst* is an indicator for those auctions which began (and ended) first in a given week (see Table 2). *Yellow Star* is an indicator for whether or not the seller has earned a "yellow star," which is awarded by eBay after achieving a feedback score of 10. *Others* is a vector representing two indicators for the number of other auctions, for the same product, running on the last day our own auction.[30] The first of which, $Others^1$, is an indicator for whether the auction had a number of competitors in the second or third quartile of the number of sellers we observed in that product market. The second, $Others^2$, is an indicator for whether the number of other auctions is in the last quartile. [31] This data was obtained by searching eBay for auctions, or Buy-it-Now[32] sales, of the same product we sell and counting the results. It should be noted that this is less accurate for fishing lures, as those products were often sold in bundles of different quantities than we sold. Finally, this model also includes a series of dummy variables for each product and week combination.

$$\begin{aligned} Price_i = {} & \beta_0 + \beta_1 BlackName_i + \beta_2 EndsFirst_i + \Omega \sum_o Others_i^o + \beta_5 YellowStar_i \\ & + \Xi(Week_{\mathrm{w}} \times Product_{\mathrm{p}}) + \varepsilon_{\mathrm{i}} \end{aligned} \tag{1}$$

The first column of Table 5 estimates Equation (1), without *Yellow Star* or its' interaction with the seller's race. The third column includes *Yellow Star*. Without controlling for feedback

[28] In addition to regressing on the final price we explicitly calculated the maximum willingness to pay of the runner-up by removing the minimum bid from the final price. This had no significant change on any of the results.

[29] In the market for Toys *Black Name* indicates a seller named either Tyrone or Jamal, instead.

[30] Alternatively, we also use the average number of auctions over the duration of our auction, though this was found to be insignificant.

[31] Formally, $Others^1$ for the race neutral market indicates a number of other sellers between three and seven and $Others^2$ indicates more than seven sellers. For the distinctively black market, $Others^1$ indicates a number of sellers between 10 and 20, while $Others^2$ indicates more than 20 sellers.

[32] A posted-price item for sale on eBay.

there is no significant effect from the seller's name. When we control for whether a seller has earned a yellow star we find that this award is significant and adds considerably to the final price sellers earn.[33] Also, the effect of having a black name is negative and significant at the ten percent level for this specification. Our black-named sellers earned, *ceteris paribus*, \$0.39 less per auction than our sellers with white names, which is significant at the five percent level. Given that the average price in this market is \$5.62, this represents a decrease of 7 percent.

The second and fourth columns of Table 5 show the results of the model in Equation (2), in which we replace the *Black Name* indicator with an indicator for each one of the four names used. The coefficients for the names can be thought of as the average price each seller received. The results of this model are consistent with Equation (1). In columns two and four we see that the coefficients for Jake and Dustin are both higher than those for Tyrone and Deshawn.

$$Price_i = \Theta\sum_{k} Name_k + \beta_1 Endsfirst_i + \Omega\sum_{o} Others_i^o + \beta_2 YellowStar_i + \Xi(Week_w \times Product_p) + \varepsilon_i \qquad (2)$$

Having already shown (by comparing difference in prices) that our results may change with the accumulation of feedback, we now attempt to capture this econometrically. We estimate Equation (3), which replaces the *Black Name* indicator with a series of interaction terms between *Black Name* and dummies for each of the three cycles. The results for this model can be seen in Table 6. Keeping with our earlier findings, these results show a significant and negative effect from having a distinctively black name in the first cycle, when sellers have little to no feedback. This translates into a loss of about \$0.71 for black-named sellers per auction. There is, however,

[33] Additional models including an interaction term between *Yellow Star* and the seller's perceived race showed that there was no significant difference between the effect of a yellow star between the races.

no significant effect from having a black name in the second or third cycles, when sellers had earned feedback.

$$Price_i = \beta_0 + \Phi\left(\sum_j BlackName_i \times Cycle_j\right) + \beta_1 Endsfirst_i + \Omega \sum_o Others_i^o + \beta_2 YellowStar_i + \Xi(Week_w \times Product_p) + \varepsilon_i \tag{3}$$

These same findings can also be seen in Table 7, which shows the results for estimating Equations (1) and (2) for each cycle separately. Once again there is a significant and negative effect on price from having a black name in the first cycle, but it is absent in subsequent cycles.

In addition, we estimate by subsamples based on sellers' feedback ratings. Columns one and two, of Table 12, estimate Equations (1) and (2) for auctions where the seller has a feedback rating less than ten. Columns three and four show the same models for the subsample of auctions where the seller has earned a yellow star by accumulating a feedback score of ten or higher. Having a black name causes a lower price for new sellers with low feedback, and has no significant effect for those who have earned a yellow star.

4.2. Market for Distinctively Black Products

In the market for distinctively black products we ran 84 auctions over 22 weeks.[34,35] The raw results, by product, can be seen in Figures Figure *4*, Figure *5*, and Figure *6*. The mean differences in prices between white- and black-named sellers in this market are shown in Table 8. A mean difference of -0.65 shows that, on average, those sellers with a distinctively black

[34] The third cycle of distinctively black products is still underway.

[35] Our results, however, consider 82 of these auctions. The highest price ($13.50) and lowest price ($1.25) Barbie auctions are identified as outliers and disregarded.

name received 65 cents more, which is significant at the five percent level for a t-test and at the ten percent level for the Wilcoxon Rank-Sum test.

Table 4**Error! Reference source not found.** shows the revenue earned in this market by race, as well as the Market Discrimination Coefficient. This shows that white-named sellers earned $201.07 in this market, while black-named sellers earned $227.01. The MDC shows that black sellers earn, on average, 11% more.

Turning to regression analysis of the final price earned for our auctions, we estimate Equation (1) for the toy market. The results are shown in Table 9. As with the results of the full model in the market for race neutral products, column one shows the model without controlling for feedback and column three includes *Yellow Star*.[36] Both show that having a distinctively black name earns a seller a significantly higher price over a seller with a white name. This is significant at the five percent level. Column three shows that having a black name earns a seller an additional $0.68, or 13 percent of the average price of $5.34, when selling distinctively black products.

The second and fourth columns of Table 9 show the results for estimating Equation (2). In both models the coefficients for Tyrone and Jamal are higher than those for Dustin and Jake. In stark contrast with the race neutral product market these models show no significant effect from the seller's feedback on the price they earn.

The results for estimating Equation (3) for this market, which look at how the effect of the seller's name varies by cycle, are shown in Table 11. Both specifications show that while the seller's name has no significant effect in the first cycle, in the second cycle there is a large,

[36] Additional models including an interaction term between *Yellow Star* and the seller's perceived race showed that there was no significant difference between the effect of a yellow star between the races.

positive, and significant effect on price from having a black name. The second specification includes whether the seller has earned a yellow star, which is again shown to be insignificant.

To further explore our findings we estimate both Equations (1) and (2) for both cycles separately, which is shown in Table 10. The first two panels estimate Equations (1) and (2), respectively, just for the first cycle. These models show a positive but insignificant effect from having a distinctively black name. Column three estimates Equation (1) for the second cycle, and shows that sellers with a distinctively black name earn \$1.40 higher price than our white-named sellers. Column four of Table 10 estimates Equation 2 for the second cycle, and finds similar results. In the third cycle sellers with a distinctively black name earn an additional \$0.97 more than white-named sellers. The coefficients for Tyrone and Jamal are both higher than those for Dustin and Jake.

5. Conclusion

We conduct a field experiment by selling matched pairs of goods on eBay where the key difference between the auctions is that one is sold under a name that is distinctively black (e.g. Tyrone or Jamal) while the other under a name that is distinctively white (e.g., Dustin or Jake). This allows us a relatively simple and clean method for identifying and quantifying racial discrimination by testing for a statistically significant difference in prices. Furthermore, by continuing to sell under the same accounts our sellers accumulate feedback – a score indicating previous successful sales where buyers are pleased with their transaction. This gives us the opportunity to determine whether the effect is due to taste-based or statistical discrimination, by testing if discrimination lessens with the development of a credible reputation.

In the race neutral product market for fishing lures we find, at first, that having a distinctively black name earns sellers a significantly lower price. However, this effect disappears over time as the sellers acquire feedback. These results are consistent with theories of statistical discrimination. Buyers paid significantly lower prices to sellers with distinctively black names when they had little other information about those sellers, as if race is a signal of quality. Once our sellers had established visible reputations as trustworthy merchants, the difference in prices between white- and black-named sellers disappeared.

In the market for distinctively black products we observed the opposite effect – sellers with a distinctively black name earned a higher price. It is also interesting to note that in this market feedback, unlike in the race neutral market, is insignificant. While this does not present enough evidence to reject the role of statistical discrimination in this market entirely, discrimination clearly operates differently in this market than in the market for fishing lures.

With so much evidence from previous studies that having a culturally distinctive name may adversely affect a person, economic theory suggests there should be a benefit to having such a unique name (Fryer and Levitt, 2004). Our findings are, to our knowledge, the first empirical evidence of this theoretical benefit to having a distinct minority name. This pattern of behavior is consistent with taste-based discrimination.

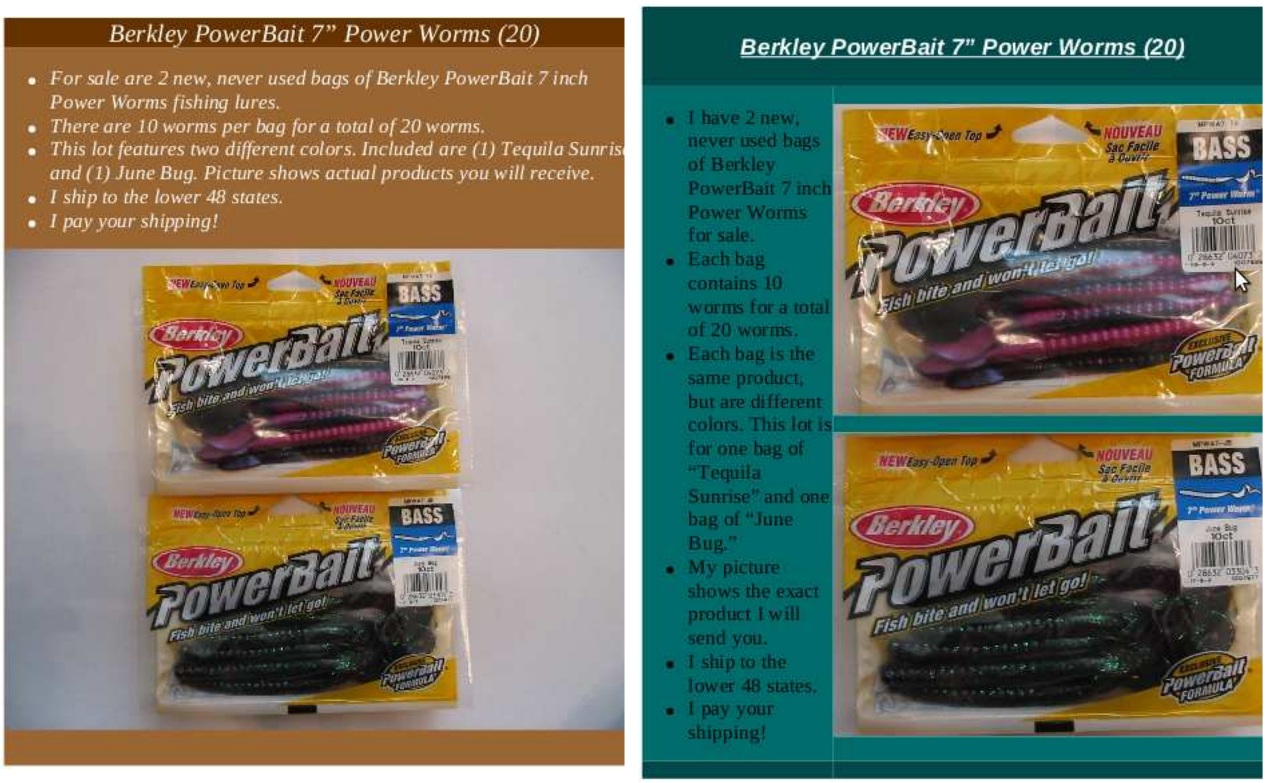
This study's results support the findings from List (2004) in that we also attribute some of the discrimination observed to statistical discrimination. In List's study race is used as a signal for the unknown reservation value of the other side of the market. This is not an issue in our experiment since our auctions are all designed with no reservation value and there is no bargaining. It is also important to note that our buyers were natural market participants, unaware that data from our transactions would be a part of an experiment. Perceived race is, in the race neutral product market, used as a signal for whether the contract would be fulfilled – that is, the good they are buying would be delivered on time and in the condition described by the seller. This fear is diminished by having a credible reputation as an honest seller.

The policy implications of our results highlight the importance of understanding the root of observed discrimination. In the case of statistical discrimination market mechanisms that support the development of trustworthy signals of reputation, such as eBay's feedback system, reduce this asymmetry in information – and by extension reduce discrimination in the market.

Appendix A – Testing Auction Descriptions

In order to ensure our auctions look natural, and that buyers are unaware that they are participating in an experiment, we use auction descriptions that vary cosmetically. While the information displayed in each auction of a given pair is the same, the font, layout, and color scheme are changed so that they appear different. See Figure 1 for an example of two such descriptions.

FIGURE 1: EXAMPLE OF DIFFERENT AUCTION DESCRIPTIONS



Concerned that those differences in the descriptions may affect the final price we designed the descriptions so that buyers would be indifferent between them.

A.1 Initial Tests

In our initial tests we asked 269 undergraduate students to look at a series of paired auction descriptions (such as those shown in Figure 1 and asked "Which of the two items would you be more likely to bid on?" For each pair we use Wilcoxon matched-pairs signed-rank tests to determine if respondents preferred one over the other.[37] Those description layouts that were chosen significantly more (or less) frequently were discarded.

From this our sellers were assigned general description layouts so that respondents were statistically indifferent between a seller's description and the descriptions assigned to the sellers of the opposite perceived race, who they compete with. For example, the seller account Dustin was assigned a description that was statistically the same as the descriptions given to Deshawn and Tyrone.

A.2 Refined Tests

After we conducted approximately 70 auctions, which indicated significant differences in price, we wanted to verify that the respondents from our initial tests held up. One concern was that participants may not have had an incentive to offer their true preferences. We conducted a second round of tests of our auctions' descriptions with incentives for honest responses. This time students and faculty from across Middle Tennessee State University were recruited to participate in an experiment for cash.

Experiment participants each received $5.00 for showing up on time. Each was shown a series of 20 pairs of auctions, 15 of which we had previously ran. The other five were for new toy products. Each participant was asked to examine both descriptions and "decide which of the two would be more likely to earn a higher price." The order of the auction pairs, and which

[37] Results from t-tests are no different.

description was first or second in the pair, was randomized to eliminate any effect the order of presentation may have had.

Possessing data on which auctions actually won for 15 of the pairs, we paid $0.50 for each correct answer. Each of the other five pairs was marked as correct for each student. The average payout was $11.50. We collected from 39 participants who rated 20 auctions each, over three sessions, which lasted an average of 30 minutes.

From these results we found only two pairs where our respondents had a statistically significant preference. The first indicates that one of the black-named sellers may have had an advertising advantage in selling Fisher Price Little People with a brown background. Data from this survey show that our respondents correctly predicted that this background would win more often. Using a Wilcoxon signed-rank test we reject that these two particular descriptions were chosen equally with a z-statistic of 1.761 (p-value: 0.0782).

Second, respondents predicted that a blue background auction selling Peek-a-Boo Barbie would win more often than a green background. The Wilcoxon test rejects the null that these two descriptions were chosen equally with a z-statistic of 2.082 (p-value: 0.0374). In this case, however, respondents predicted incorrectly – the green background, which was assigned to a white-named seller, actually won more frequently for this product.

From these results we have decided to attempt to replicate our auctions sold with the preferred backgrounds. Data collection for this is still underway.

References

Akerlof, George A. 1970. "The Market for 'Lemons': Quality Uncertainty and the Market Mechanism." *The Quarterly Journal of Economics*, 84(3): 488-500.

Akerlof, George A. and Kranton, Rachel E. 2000. "Economics and Identity." *The Quarterly Journal of Economics*, 115(3): 715-753.

Altonji, Joseph G. and Blank, Rebecca M. 1999. "Race and Gender in the Labor Market." *Handbook of Labor Economics*, in: O. Ashenfelter & D. Card (ed.) , Handbook of Labor Economics, edition 1, volume 3, chapter 48, pages 3243-3259 Elsevier.

Arrow, Kenneth J. 1973. "The Theory of Discrimination." In *Discrimination in Labor Markets*, eds. Orley Ashenfelter and Albert Rees, eds. Princeton, NJ: Princeton University Press, 3-33.

Ayres, Ian and Peter Siegelman. 1995. "Race and Gender Discrimination in Bargaining for a New Car." *American Economic Review*, 85(3): 304-321.

Bajari, Patrick and Ali Hortacsu. 2003. "The winner's curse, reserve prices, and endogenous entry: empirical insights from eBay auctions." *The RAND Journal of Economics,* 34(2): 329-355.

Bajari, Patrick and Ali Hortacsu. 2004. "Economic insights from Internet Auctions*." Journal of Economic Literature*, 32: 457-486.

Becker, Gary S. 1957. *The Economics of Discrimination*. University of Chicago Press: Chicago and London.

Bertrand, Marianne and Sendhil Mullainathan. 2004. "Are Emily and Greg More Employable than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination." *American Economic Review*, 94(4): 991-1013.

FBI. 2008. "2008 Internet Crime Complaint Center Annual Report" Online: http://www.ic3.gov/media/annualreports.aspx

Fryer, Roland G. and Steven D. Levitt. 2004. "The Causes and Consequences of Distinctively Black Names." *Quarterly Journal of Economics*, 119(3): 767-805.

Goldberg, Pinelopi K. 1996. "Dealer Price Discrimination in New Car Purchases: Evidence from the Consumer Expenditure Survey." *Journal of Political Economy*, 104(3): 622-654.

Heckman, James J. 1998. "Detecting Discrimination." *Journal of Economic Perspectives*, 12(2): 101-116.

Hortacsu, Ali; Martinez-Jerez, A.; Douglas, Jason. 2009. "The Geography of Trade in Online Transactions: Evidence from eBay and MercadoLibre." *American Economic Journal: Microeconomics*, 1(1): 53-74.

Hossain, Tanjim and John Morgan. 2006. "…...Plus Shipping and Handling: Revenue (Non) Equivalence in Field Experiments on eBay," *Advances in Economic Analysis & Policy*, 6(2): 1-27

Katkar, Rama and Reiley, Havid H. 2005. "Public versus Secret Reserve Prices in eBay Auctions: Results from a Pokemon Field Experiment." *NBER Working Paper,* No. W8183.

Levitt, Steven D. and Stephen J. Dubner. 2005. *Freakonomics: A Rogue Economist Explores the Hidden Side of Everything*. Harper Collins: New York.

List, John A. 2004. "The Nature and Extent of Discrimination in the Marketplace: Evidence form the Field." *Quarterly Journal of Economics*, 119(1): 49-89.

Lucking-Reiley, David, Doug Bryan, Naghi Prasad, and Daniel Reeves. 2007. "Pennies from eBay: The Determinants of Price in Online Auctions." *Journal of Industrial Economics*, 55(2): 223-233.

McAfee, R. Preston and McMillan, John. 1987. "Auctions and Bidding." *Journal of Economic Literature*, vol. 25 (2), p. 699-738.

Phelps, Edmund S. 1972. "The Statistical Theory of Racism and Sexism." *American Economic Review*, 62(4): 659-661.

Riach, P. A. and Rich, J. 2002. "Field Experiments of Discrimination in the Market Place." *The Economic Journal,* 112(483): F480-F518.

Roth, Alvin E. and Axel Ockenfels. 2002. "Last-Minute Bidding and the Rules for Ending Second-Price Auctions: Evidence from eBay and Amazon Auctions on the Internet." *American Economic Review*, 92(4): 1093-1103.

Yinger, John. 1986. "Measuring Racial Discrimination with Fair Housing Audits: Caught in the Act." *American Economic Review*, 76(5): 881-893

TABLE 1: PRODUCTS SOLD

Product	Average Price
Race Neutral Market	
ChatterBait	7.38
ChatterFrog	4.50
Culprit 7.5" Worms	5.65
Strike King Mini-King Spinnerbait	3.98
Berkley Powerbait 7" Worms	5.93
Strike King Spinnerbait	6.88
Stanley Spinnerbait	5.65
Black Market	
Fisher Price Little People	3.10
Mattel Beach Party Barbie	5.49
Mattel Peek a Boo Barbie	3.79
Fisher Price Dollhouse Figures	7.93

TABLE 2: TIMING OF AN AUCTION CYCLE

	Product 1		Product 2	
Week	Thursday/ Tuesday	Saturday/ Thursday	Thursday/ Tuesday	Saturday/ Thursday
1	Jake	DeShawn	Tyrone	Dustin
2	DeShawn	Jake	Dustin	Tyrone
3	DeShawn	Dustin	Jake	Tyrone
4	Dustin	DeShawn	Tyrone	Jake
5	Dustin	Tyrone	DeShawn	Jake
6	Tyrone	Dustin	Jake	DeShawn
7	Jake	Tyrone	DeShawn	Dustin
8	Tyrone	Jake	Dustin	DeShawn

Notes: In the market for toys the name 'Jamal' is used in place of the name 'DeShawn.'

TABLE 3: MEAN PRICE DIFFERENCES BETWEEN WHITE AND BLACK NAMES FOR THE MARKET FOR A RACE NEUTRAL PRODUCT

	N	Mean	Standard. Error	Standard Deviation	p-value for t-test: mean > 0	p-value for sign test: mean > 0	p-value for Wilcox: mean ≠ 0
Cycle 1	16	0.75	0.3455	1.3821	0.0232	0.0287	0.0461
Cycles 1 & 2	32	0.46	0.2830	1.6013	0.0584	0.1002	0.2001
All Cycles	48	0.25	0.1971	1.3658	0.1941	0.1510	0.4508
Cycle 1	16	0.75	0.3455	1.3821	0.0232	0.0287	0.0461
Cycle 2	16	0.16	0.4476	1.7902	0.3645	0.5982	0.9176
Cycle 3	16	-0.16	0.1944	0.7776	0.7936	0.5982	0.5013
Worms	24	0.13	0.2396	1.1737	0.2934	0.4159	0.9203
Spinners	24	0.37	0.3305	1.6193	0.1388	0.1537	0.3457

Notes: Price difference is calculated by subtracting the price earned by the black-named seller in a given pair of auctions from the price earned by the white-named seller.

TABLE 4: COMPARING REVENUE AND MARKET DISCRIMINATION COEFFICIENT

	White Profit	Black Profit	Difference	MDC
All Lures	$275.64	$263.65	$11.99	0.045
Worms	139.39	136.22	3.17	0.023
Spinners	136.25	127.43	8.82	0.069
All Toys	201.07	227.01	-25.94	-0.114
Barbie	62.18	73.23	-11.05	-0.151
Dollhouse	94.03	108.38	-14.35	-0.132
Other Toys	44.86	45.40	-0.54	-0.012

TABLE 5: MARKET FOR A RACE NEUTRAL PRODUCT FULL MODEL

	(1)		(2)		(3)		(4)	
Black Name	-0.2152				-0.3880	*		
	(0.2099)				(0.2156)			
Ends First	0.2992		0.2981		0.2934		0.2895	
	(0.2151)		(0.2197)		(0.2065)		(0.2093)	
Others 1	-0.5530		-0.5600		-0.4983		-0.5109	
	(0.4725)		(0.4876)		(0.4541)		(0.4649)	
Other 2	-0.6061		-0.5684		-0.5495		-0.4360	
	(0.7678)		(0.7932)		(0.7372)		(0.7575)	
Yellow Star					1.3546	**	1.4389	**
					(0.6038)		(0.5953)	
Tyrone			5.5302	***			5.4274	***
			(0.4307)				(0.4125)	
Deshawn			5.5238	***			5.4202	***
			(0.5136)				(0.4911)	
Dustin			5.8067	***			6.0140	***
			(0.4672)				(0.4535)	
Jake			5.6768	***			5.6432	***
			(0.4645)				(0.4427)	
N	96		96		96		96	
R^2	0.42		0.40		0.47		0.57	
LL	-103.64		-103.54		-98.66		-97.78	

Notes: Standard Errors are in parentheses. *, **, and *** indicated statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 6: FISHING TIMING

Black x Cycle 1	-0.7127	*	-0.7127	**
	(0.3550)		(0.3337)	
Black x Cycle 2	-0.1631		-0.8410	*
	(0.3538)		(0.4207)	
Black x Cycle 3	0.2383		0.2383	
	(0.3586)		(0.3371)	
Ends First	0.3038		0.3038	
	(0.2115)		(0.2115)	
Others 1	-0.5963		-0.5963	
	(0.4676)		(0.4396)	
Others 2	-0.6509		-0.6509	
	(0.7569)		(0.7115)	
Yellow Star			1.8077	**
			0.6870	
N	96		96	
R^2	0.44		0.51	
LL	-99.92		-92.90	

Notes: Standard Errors are in parentheses. *, **, and *** indicated statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 7 RACE NEUTRAL MARKET CYCLES SEPARATE

	Cycle 1				Cycle 2				Cycle 3			
Black Name	-0.7130	*			0.1650				0.2453			
	(0.3543)				(0.4251)				(0.1944)			
Ends First	0.7688	*	0.7534	*	0.2537		0.2537		0.2630		0.2565	
	(0.3661)		(0.3847)		(0.4251)		(0.4551)		(0.2084)		(0.2281)	
Others 1	-0.5914		-0.4902		-1.8050		-0.0425		-0.6521	*	-0.6262	
	(0.7145)		(0.7586)		(1.2023)		(1.4392)		(0.3477)		(0.3995)	
Others 2	-0.9058		-0.7323		0.2500		0.1275		-0.6521		-0.5910	
	(1.0354)		(1.1254)		(1.2023)		(1.3653)		(0.6387)		(0.7082)	
Tyrone			4.9676	***			5.9819	***			6.2914	***
			(0.5396)				(1.0177)				(0.7240)	
Deshawn			5.2219	***			6.2219	***			6.4849	***
			(0.7294)				(1.2041)				(0.5955)	
Dustin			6.0704	***			6.1094	***			6.1813	***
			(0.5979)				(1.2041)				(0.7051)	
Jake			5.5578	***			5.7644	***			6.1110	***
			(0.6137)				(1.0177)				(0.5610)	
N	32		32		32		32		32		32	
R^2	0.25		0.18		0.38		0.29		0.80		0.77	
LL	-33.09		-37.79		-38.07		-37.79		-9.74		-9.36	

Notes: Standard Errors are in parentheses. *, **, and *** indicated statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 8: MEAN PRICE DIFFERENCE BETWEEN WHITE AND BLACK NAMES FOR DISTINCTIVELY BLACK MARKET

					p-value Ha: mean < 0		
	N	Mean	Standard. Error	Standard Deviation	t-test	Sign test	Wilcox
Cycle 1	16	0.0606	0.3745	1.4980	0.5632	0.8491	0.7367
Cycles 1&2	30	-0.5023	0.3659	2.0042	0.0902	0.5747	0.3763
All	40	-0.6485	0.2979	1.8842	0.0178	0.2088	0.0890
Cycle 1	16	0.0606	0.3745	1.4980	0.5632	0.8491	0.7367
Cycle 2	14	-1.1457	0.6288	2.3528	0.0458	0.2905	0.1313
Cycle 3	10	-1.0870	0.4644	1.4644	0.0220	0.0547	0.0365
Barbie	13	-0.8500	0.4331	1.5617	0.0367	0.0730	0.0866
Dollhouse	13	-1.1039	0.6666	2.4034	0.0618	0.5000	0.1724
Other Toys	14	-0.0386	0.4157	1.5553	0.4637	0.5000	1.0000

Notes: Price difference is calculated by subtracting the price earned by the black-named seller in a given pair of auctions from the price earned by the white-named seller.

TABLE 9: DISTINCTIVELY BLACK MARKET FULL MODEL

Black Name	0.6529	**			0.6836	**		
	(0.3173)				(0.3155)			
Ends First	-0.2571		-0.2962		-0.3712		-0.3812	
	(0.3131)		(0.3204)		(0.3230)		(0.3312)	
Others 1	0.3401		0.1629		0.4848		0.3202	
	(1.9711)		(2.0389)		(1.9574)		(2.0442)	
Others 2	-1.1157		-1.0375		-0.8876		-0.8676	
	(2.7923)		(2.8330)		(2.7740)		(2.8371)	
Yellow Star					-1.4757		-1.2451	
					(1.1509)		(1.2325)	
Tyrone			3.8377	*			3.8115	*
			(2.1369)				(2.1365)	
Jamal			4.4475	*			4.2370	*
			(2.2436)				(2.2536)	
Dustin			3.4010				3.3024	
			(2.3041)				(2.3055)	
Jake			3.6279				3.4242	
			(2.1843)				(2.1929)	
N	82		82		82		82	
R^2	0.72		0.71		0.73		0.71	
LL	-108.99		-107.84		-107.14		-106.63	

Notes: Standard Errors are in parentheses. *, **, and *** indicated statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 10: DISTINCTIVELY BLACK MARKET TIMING SEPARATELY

	Cycle 1		Cycle 2		Cycle 3	
Black Name	-0.0784		1.4044 *		0.9743 *	
	(0.4015)		(0.6923)		(0.5013)	
Ends First	-0.3641	-0.4232	0.3856	-0.0376	-0.6026	-0.6312
	(0.4015)	(0.3818)	(0.6923)	(0.7272)	(0.4756)	(0.4948)
Others 1	0.2843	0.5168	-1.3200	1.6819	-1.8721	-1.7115
	(1.6586)	(1.6347)	(2.1725)	(2.5839)	(1.0868)	(1.1773)
Others 2			-4.1700	0.9624	3.8650 ***	2.3741
			(3.6026)	(3.2624)	(1.0575)	(1.3528)
Tyrone		3.0192 *		6.5124 ***		6.2844 ***
		(1.6869)		(1.8540)		(0.8844)
Jamal		1.4602		8.5572 ***		5.7697 ***
		(3.1630)		(2.4928)		(1.1388)
Dustin		2.3555		6.8914 **		5.6068 ***
		(1.9553)		(2.5192)		(0.9190)
Jake		3.8653 **		6.0655 **		4.3034 **
		(1.7477)		(2.3565)		(1.2697)
N	32	32	30	30	20	20
R^2	0.29	0.37	0.47	0.47	0.74	0.72
LL	-35.14	-40.38	-43.74	-40.52	-20.33	-18.10

Notes: Standard Errors are in parentheses. *, **, and *** indicated statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 11: DISTINCTIVELY BLACK MARKET TIMING EFFECTS

Black x Cycle 1	-0.0907		-0.0826	
	(0.4839)		(0.4762)	
Black x Cycle 2	1.2741	**	1.3717	**
	(0.5241)		(0.5201)	
Black x Cycle 3	1.0212		1.0077	
	(0.6250)		(0.6152)	
Ends First	-0.1788		-0.3007	
	(0.3073)		0.3137	
Others 1	-0.4819		-0.3519	
	(1.9613)		1.9322	
Others 2	-2.6372		-2.4828	
	2.8306		2.7877	
Yellow Star			-1.6347	
			1.1179	
N	82		82	
R^2	0.74		0.71	
LL	-71.63		-69.80	

Notes: Standard Errors are in parentheses. *, **, and *** indicated statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 12: RACE NEUTRAL MARKET BY FEEDBACK

	New Sellers				Yellow Star			
Black Name	-0.6108	*			-0.1569			
	(0.3293)				(0.2887)			
Ends First	0.5516		0.5763		-0.0253		-0.0621	
	(0.3371)		(0.3387)		(0.3050)		(0.3104)	
Others 1	-0.5627		-0.5029		-0.3258		-0.1422	
	(0.7768)		(0.7865)		(0.5663)		(0.5945)	
Others 2	-0.7685		-0.4313		-0.3258		-0.5018	
	(1.1180)		(1.1469)		(1.0594)		(1.0992)	
Tyrone			5.2553	***			7.5621	***
			(0.5239)				(0.9582)	
Deshawn			4.9372	***			7.9046	***
			(0.7011)				(1.1355)	
Dustin			6.1302	***			7.4771	***
			(0.5709)				(1.1115)	
Jake			5.2894	***			8.1963	***
			(0.6157)				(1.0996)	
N	50		50		46		46	
R^2	0.35		0.35		0.55		0.54	
LL	-53.37		-50.98		-35.90		-33.40	

Notes: Standard Errors are in parentheses. *, **, and *** indicated statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure 2: Auction Prices by Pair, Spinners

Figure 3: Auction Prices by Pair, Soft Plastic Worm Lures

Figure 4: Auction Prices by Pair, Barbie

Figure 5: Auction Prices by Pair, Dollhouse Figures

Figure 6: Auction Prices by Pair, Little People