Why Are Women Penalized in Product Markets?

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Abstract
Previous research using data from eBay found that women receive lower prices than men when selling the exact same products. The current project explores why this gender gap obtains and why some products have larger gender price gaps than others. To answer these questions, we exploit the variation in the gender price gap across products found in the earlier eBay data together with new survey data on the perceptions people have about seemingly male-typed and female-typed products and about people’s uncertainty about the prices of products. We show that women are penalized more for selling products that are perceived to be typically owned by men compared to products that are perceived to be typically owned by women. We further demonstrate that the effects of gender stereotypes are greater when buyers’ uncertainty increases: when buyers are uncertain about their willingness to pay for a product or about its market price, women sellers are penalized more.

Keywords
gender, product market

In this project, we investigate the mechanisms generating price differences between female and male sellers in product markets. We build on the findings of a previous study using eBay auction data that found that women receive lower prices than men when selling the exact same new products. The magnitude of the observed gender price gap varies across products such that for some products, gaps in the prices received by women and men are greater than for other products. Here, we exploit the variation in the gender price gap across products to understand what traits of products and sales generate greater gender price gaps. We wish to understand the role of gendered stereotypes and cultural scripts about types of products in generating gender inequality. In doing so, we build on the literature in social psychology that emphasizes the roles of sex stereotypes and cultural scripts in generating gender inequality (Ridgeway 2011; Ridgeway and Correll 2004).

Specifically, we ask whether the gender price gap is greater for seemingly male-typed products compared to seemingly female-typed products; for example, we wonder whether the gender price gap is greater in sales of drills compared to sales of sewing machines. We also wonder whether sellers rely more on sex stereotypes and cultural scripts when uncertainty is greater. We therefore ask whether price gaps are greater in sales when buyers are uncertain about how much the product should cost.

Answers to these questions are important because while scholars have produced an impressive body of theoretical and empirical evidence about the extent and causes of gender inequality in labor markets (Blau 2016; Blau and Kahn 2000; Eagly and Carli 2007; England and Folbre 2005; Ridgeway 2011), we know surprisingly little about how gender operates in product markets. If women experience similar disadvantages in product markets as they do in labor markets, the negative effects of gender in economic life are greater than previously understood. Moreover, understanding the mechanisms that produce gender price gaps in product markets would enable us to better understand and address gender inequality in product markets but also in other arenas, like the labor market. Finally, unlike with labor markets, discrimination in product markets is not regulated by law, so whereas employment sex discrimination is prohibited, peer-to-peer sex discrimination in product markets is not.

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In this article we first review the literature on the effects of gender in product markets, describing in some detail the one recent study—on which we build and further explore—that shows that women are, in fact, disadvantaged as sellers compared to men when selling the exact same new product on eBay (Kricheli-Katz and Regev 2016, hereinafter referred to as the “eBay study”). This study found that, on average, women received about 80 cents for every dollar a man received when selling an identical new product and 97 cents when selling the same used product (see Table A1 in the appendix). The magnitude of the observed gender price gap varied across products.

Utilizing the variation in the observed gender price gap across products, in the current study, we first test whether women are penalized more for selling seemingly male-typed products compared to seemingly female-typed products. We are curious whether, for example, the gender price gap for drills is greater than the gender price gap for sewing machines. We conceptualize seemingly male-typed products as products that are believed to be typically owned (and sold) by men and seemingly female-typed products as products that are believed to be typically owned (and sold) by women. We predict that when there is a perceived lack of fit between the gender of the actual owner and beliefs about who the prototypical owner should be, penalties arise. Thus, penalties are greater when products are perceived to be typically owned by men compared to by women.

In order to investigate this hypothesis, we first determine which products are perceived to be male-typed products and which are perceived to be female-typed products. People may think, for example, that the prototypical owner of a drill is a man and that the prototypical owner of a sewing machine is a woman. We ask people to report how likely the owner of the different products in our data is to be a woman or a man and test whether respondents tend to agree with each other. We then use these perceptions to test whether the gender price gaps that were observed in the previous eBay study are greater for male-typed products (those typically owned by men) compared to female-typed products (those typically owned by women).

We also hypothesize that lack of information regarding the value of products increases the gender price gap for new products. The logic behind this prediction comes from literature that shows that decision makers rely on gender stereotypes and cultural scripts more under conditions of uncertainty. Thus, disadvantages for women are greater when less information is available (Heilman and Haynes 2005; Kalev 2009; Ridgeway 2011; Ridgeway and Correll 2004; Sterling and Fernandez 2018; Uhlmann and Cohen 2007). In the case of product markets, when buyers are uncertain about the market price, stereotypes and cultural scripts about gender influence perceptions of the value of the product and the transaction, thereby influencing how much buyers are willing to pay for the specific product being sold by a female or a male seller.

To test the two mechanisms, we combine the price data from the eBay study that include the gender price gap for 306 products with data from two original surveys and use these combined data to explore our predictions. The two surveys document people’s perceptions about the traits of the 306 products: whether the products are seemingly male typed or female typed and the uncertainty about their market prices. Responses of the participants in the surveys are then used in regression models to explain the gender price gaps obtained in the eBay study. By using this innovative research design that combines actual market data with survey data, we are able to explain the mechanisms generating real-world price gaps with survey evidence.

**Do Women Receive Lower Prices Than Men?**

To date, there has been comparatively little evidence regarding the effect of gender in product markets. There is some evidence, based on the findings of field experiments, that suggests discrimination against female buyers in product markets (Ayres and Siegelman 1995; Riach and Rich 2002). Studies have documented a related gender gap in venture capital funding and in loan granting in the United States. These studies have shown that female entrepreneurs are disadvantaged compared to their male counterparts in getting venture capital funding and loans (Thébaud 2015; Tinkler et al. 2015). Studies have further suggested that the gap is generated by biases in the behavior and evaluations of investors (Balachandra et al. 2013; Clark 2008; Gorbatai & Nelson 2015; Huang, Friderger, and Pearce 2013; Kanze et al. 2018) and by differences in the behavior of female and male entrepreneurs (Cliff 1998; Loscocco et al. 1991; Morris et al. 2006).

But how do female **sellers** fare? A recent study analyzing data on all the eBay auction transactions for 420 of the top-selling products from 2009 to 2012 found that female sellers are disadvantaged in product markets (Kricheli-Katz and Regev 2016). Specifically, the study found that in eBay auctions, women receive a smaller number of bids and lower final prices than do equally qualified male sellers of the exact same product (and controlling for the gender of the buyer, the sentiments in the text, the state, the date, the time, and other relevant characteristics of the auction). Women received, on average, about 80 cents for every dollar a man received when selling the exact same new product and 97 cents when selling the same used product (Kricheli-Katz and Regev 2016) (see Table A1 in the appendix). Note that the classification of products in the data is highly refined—a new blue iPod shuffle, second generation, for instance—so that comparisons between women and men are for the exact same products. Hence, results regarding new products are particularly informative as products are identical and new, so quality-related explanations for the gender price gap become irrelevant. Note also that the data set used for the analyses contains only...
auctions—where sellers and buyers do not negotiate with each other. Thus, differences in the negotiation skills of women and men or in sellers’ willingness to accept are irrelevant.

As a policy, eBay does not reveal the gender of its users. Nonetheless, the authors were able to show in a separate experiment that people were quite accurate in guessing the actual gender of the seller (provided to the researchers by eBay) from contextual cues in the product listing (such as the other items a person is selling).

Yet, while Kricheli-Katz and Regev (2016) were able to show that female sellers were disadvantaged, the data could not answer the question of why female disadvantage obtained. The study did find that the gender price gap was larger for some products than others. We now utilize these differences across products and merge it with novel survey data to evaluate whether women are penalized more for selling seemingly male-typed products compared to seemingly female-typed products and whether when uncertainty is greater, buyers rely more on their gender stereotypes.

**Gendered Perceptions of Owners of Products**

We start our investigation by exploring people’s perceptions of whether products are male typed or female typed. We asked people how likely is the owner of each product in our data to be a woman.

Why would people believe that some products are more likely to be owned by women and others to be owned by men? Studies have shown that people tend to automatically and unconsciously sex-categorize others in social interactions (Ito and Ueland 2003) in order to understand “who” the other is. We tend to immediately assign a gender to every person we interact with—whether in person or virtually—and then to draw on our cultural scripts about gender to predict the other’s traits and future behavior. In fact, in the eBay study, the authors experimentally showed that people accurately sex-categorize sellers. If sellers are routinely sex-categorized, cultural scripts about whether sellers or owners of products are likely to be women or men may develop. For example, in current U.S. society, cultural scripts about products and their usage may lead people to associate drills with male owners (and users) and sewing machines with female owners (and users).

“Lack of Fit”: Penalties for Sellers Deviating from Gendered Perceptions of Prototypical Owners

If, indeed, people hold consistent and defined cultural beliefs about prototypical owners of products, we would expect such beliefs to interact with beliefs about actual sellers, affecting the prices people offer. For example, if golf clubs are believed to be typically owned by men, then when women attempt to sell such products, a perceived lack of fit between the product and the actual seller may arise. As a result, female sellers of such golf clubs may receive lower prices compared to male sellers. A perceived lack of fit may also arise when a man is selling a product that is believed to be typically owned by women, like a Disney movie, for example.

We borrow the term *lack of fit* from the literature in social psychology. In the case of gender, women are often not seen as suited for some jobs, especially in male-typed fields, because they are perceived to lack the traits (like aggressiveness) that the organization values. For example, Lyness and Heilman (2006) find that women are less likely to be hired and, when hired, are more likely to receive lower evaluations for positions that are prototypically held by men compared to when positions are prototypically held by women. In the context of product markets, lack of fit occurs when the perceived traits of prototypical owners are not perceived to overlap with traits of actual owners. When developing this concept in the context of market, we build on the literature that suggests that the social status of owners of products affects the perceived value of the products themselves. The value theory of power developed by Thye (2000) suggests that exchangeable objects owned by high-status actors are perceived to be more valuable when relevant to positive status characteristics. Building on this conceptualization, here we argue that the high status of male sellers affects the prices people are willing to pay for products, especially when the products are perceived to be male-typed products.

**Uncertainty**

One reason to expect that buyers will rely on cultural beliefs about the characteristics of owners of products in their market interactions is that market interactions tend to involve uncertainty about value and prices. Under conditions of uncertainty, people are more likely to draw on widely shared beliefs, such as stereotypes and cultural scripts (Correll 2004; Correll et al. 2017; Heilman and Haynes 2005; Kalev 2009; Podolny 2008; Reskin and McBrier 2000; Sterling and Fernandez 2018; Uhlmann and Cohen 2007). Thus for example, research has shown that female lawyers were promoted less compared to men when the job involves uncertainty (Gorman 2006).

If a similar process happens in product markets, when buyers are uncertain about prices or the quality of products, they are likely to look for “clues”—like the type of owner, the product, and the fit between them—that would help them decide how much they are willing to pay for a product. This means that when buyers are uncertain about price or quality, they may be more interested in who the owner is.

According to the prevailing cultural scripts about gender in current U.S. society, women are often perceived as less competent than men (Fiske et al. 2002; Ridgeway 2011; Ridgeway and Correll 2004). Thus, when buyers are uncertain about price
or quality of new products, they evaluate products sold by women as less valuable compared with buyers who evaluate the same products but are less uncertain.

When products are used, there is potentially more uncertainty, since a buyer can be uncertain about not only the price of a product but also its condition. Thus, compared with new products, buyers of used products are more dependent on the descriptions of products that the sellers provide. Therefore, buyers of used products likely search for additional clues that would help them assess whether they can trust the seller and the description. Research has shown that women are stereotypically viewed as more trustworthy than men (Fiske et al. 2002). Indeed, the eBay study found that women were ranked by buyers as better at describing the items they are selling compared to men (Kricheli-Katz and Regev 2016). It follows, then, that with used products, the more uncertain buyers are regarding the condition of the product, and the more dependent they are on the description sellers provide, the more they would trust women compared to men and the smaller the gender price gap would be.

Since products vary by the level of uncertainty associated with their value (e.g., there is less uncertainty about the value of a $100 gift card compared with a painting), they vary in the need for buyers to search for “clues” contained in shared cultural beliefs. Thus, we predict that the more uncertain buyers are about the value of a product, the more they would rely on cultural beliefs about the specific owner when deciding how much to pay for a product. For new products, we predict that more uncertainty would increase the gender price gaps because the relevant stereotypes and cultural scripts are that women are less competent and less status worthy. For used products, we predict that more uncertainty would decrease the gender price gaps because the relevant stereotypes and cultural scripts are that women are more trustworthy and tend to handle products better.

Data and Method

Overview

We created a data set that combines data on the gender price gap of 306 of the bestselling new and used products from the eBay study described earlier (Kricheli-Katz and Regev 2016) with original data from two surveys. The first survey randomly assigns participants to evaluate new or used products and to report their perceptions of the gender of the prototypical sellers of the products as well as their perceptions of the competence and warmth associated with the prototypical sellers of these products. These perceptions are then used to predict the gender price gap of the products from the eBay study. The second survey randomly assigns participants to evaluate new or used products and to report their uncertainty regarding the prices of products. Participants’ uncertainty is then used to predict the gender price gap of the used and new products.

Gender Price Gap Data

The original eBay data included all auctions of 420 bestselling products in the years 2009 to 2012. Each product appeared in the data both as a new product and as a used product. These data revealed that on average, women received 80 cents for every dollar men received for selling the same new products and about 97 cents for selling the same used product. Importantly for the current article, the gender price gap varied by the type of product being sold. For our analysis, we use only the products—either new or used—that were uniquely identifiable by a photo, resulting in a data set of 306 bestselling products, 99 of which are new and 207 that are used.

For each product, there is a unique gender price gap. The gender price gap is the regression coefficient obtained for being a female seller in an ordinary least squares (OLS) regression model predicting the price of product when controlling for all other transaction characteristics (such as seller’s reputation, experience, number and type of pictures, time and duration of auction, etc.; for complete details, see Kricheli-Katz and Regev 2016). In other words, we use the results of 306 different regression models—a separate model for each product in the data set. Thus, our data set contains the “female” coefficients of 306 different OLS regression models.¹ Note that the variable we use in the current analysis equals zero when gaps between women and men in the original data set were statistically insignificant. For the 306 products used in this study, the average “female” coefficient is a negative 2.6%. In the analysis, we also use the final auction prices of products from the original eBay data (the variable price). We combined these two variables from the eBay data set with the data from the two surveys. In Table 1, we report the variables we use in the analysis, by the data source.

Surveys and Measures

Two thousand thirteen participants from Amazon Mechanical Turk were randomly assigned to one of the two surveys and to a condition within each survey. We randomly assigned participants to the two surveys to ensure that participants participated in only one survey. Each survey had participants rate products on different dimensions, described later. These perceptions from the survey data were then aggregated across participants and used to predict the price gap between female and male sellers obtained in the eBay study. At the

¹For each of the 306 products, the results of an ordinary least squares regression model predicting the effects of being a female seller on the final price were obtained (controlling for the characteristics of sellers and transactions). The 306 “female seller” coefficients are the gender price gaps we use in our analyses. We also use the intercepts from these 306 regressions as the products’ prices on eBay (net of the characteristics of sellers and transactions).
end of each survey, participants answered a series of demographic questions and were directed to a webpage where they entered payment information (for the demographics of participants, see Table A2 in the appendix). Finally, we conducted a third survey to further investigate the effects of gendered perceptions of used products on the gender price gap. The methodology and results of this third study are reported in the appendix.

**Study 1: Lack of Fit**

In study 1, we test for the “lack-of-fit” hypothesis. We explore whether gender price gaps are greater when products are male typed compared to female typed—that is, when sales are of drills compared to sewing machines. In survey 1, participants (N = 1,041) were randomly assigned to one of two conditions, which varied by whether they evaluated new or used products. They were then presented with a photo of a product that was described as either used or new, depending on condition, and were asked whether the prototypical owner-seller of the product was likely to be female on a 7-point scale ranging from much more likely to be a man to much more likely to be a woman. They were also asked to report whether the prototypical owner-seller of the product was likely to be competent, confident, intelligent, pleasant, sincere, high-status worthy, tolerant, and warm (all on scales of 1 to 7). Each participant was shown five different products, randomly drawn from the larger data set.

We aggregated the responses of participants by product and generated variables that represent the average score for each item. This resulted in a data set in which the unit of analysis is a product. We then constructed, for each product, a “likely female owner” dummy variable that reflects whether on average, participants thought the owner of the product was more likely female than male. This dummy variable equals 1 if the average response to the question of whether the prototypical owner-seller of the product was likely to be female was greater than the median. As can be seen in Table 1, the mean of the “likely female owner” variable is 0.52. We use this dummy variable because the distribution of the original 7-point-scale aggregated answers was bimodal with two distinct picks (see Figure A1 in the appendix). In order to make sure that our transformation did not bias the results, we estimated each model in which the dummy variable is used also with two dummy variables generated in correspondence to the original distributions’ peaks. Results remained the same.

**Results**

Participants were relatively consistent as to whether they believed the likely owner of a product was a woman or a

| Variable | M    | SD    | Min. | Max.     |
|----------|------|-------|------|----------|
| eBay data |      |       |      |          |
| Female–male gap | −0.03 | 0.19  | −2.85 | 0.21     |
| Used      | 0.68 | 0     | 0    | 1        |
| Price     | 110.81 | 135.73 | 3.91 | 956.13   |
| Survey 1 |      |       |      |          |
| Likely female owner | 0.52 | 0     | 0    | 1        |
| Competent owner | 4.69 | 0.43  | 3.20 | 5.67     |
| Confident owner | 4.80 | 0.41  | 3.60 | 5.81     |
| Intelligent owner | 4.60 | 0.45  | 3.20 | 5.87     |
| Pleasant owner | 4.43 | 0.43  | 3.30 | 5.86     |
| Sincere owner | 4.48 | 0.38  | 3.20 | 5.62     |
| High-status owner | 4.30 | 0.60  | 2.75 | 5.87     |
| Tolerant owner | 4.37 | 0.43  | 3.00 | 5.46     |
| Warm owner | 4.29 | 0.50  | 3.06 | 5.60     |
| Competence composite | 4.57 | 0.42  | 3.40 | 5.63     |
| Warmth composite | 4.39 | 0.40  | 3.23 | 5.58     |
| Survey 2 |      |       |      |          |
| Uncertain about price | 4.15 | 0.76  | 1.92 | 6.33     |
| Interested in prices others pay | 5.12 | 0.75  | 2.58 | 6.80     |
| Interested in who the owner is | 3.40 | 0.72  | 1.75 | 5.40     |
| Survey 3 |      |       |      |          |
| Familiarity gap (only for used products) | −0.23 | 1.25  | −3.44 | 3.37     |
| Usage gap (only for used products) | −0.08 | 1.17  | −3.53 | 3.43     |

Note: N = 306 products (207 used and 99 new).
man. The standard deviation of participants’ assessment of the likelihood that the product owner-seller was a woman was on average 1.2 on a 7-point scale. The variation in participants’ responses tended to be greater for used products compared with new products.

The results from OLS regression models predicting the gender price gap on eBay by the perceived gender of the prototypical owner of the product are presented in Table 2.

As can be seen, the gender price gap for new products is affected by whether products are male typed or female typed: when new products are perceived to be typically owned by men, the price gap between female and male sellers increases. More specifically, when new products are perceived to be typically owned by men, the gender price gap increases by 0.085 ($p < .05, N = 306$). In other words, when the new product is a male-typed product, women who sell the product receive an additional 8.5% of a price penalty compared to when the product is a female-typed product. Note that in all the models predicting the gender price gap, we control for the prices of the products on eBay (net of the effects of the characteristics of sellers and transactions). Thus, the effects we observe for selling products that are perceived to be typically owned by men are generated when prices of products are held constant. To the degree to which prices reflect prestige, we also hold prestige constant in our models.

Whereas with new products the gender price gap is affected by whether products are male typed or female typed, this is not the case for used products (0.085 – 0.081 is not significantly different from zero). To better understand the effects of selling products that are perceived to be typically owned by men in transactions for the sale of used products, we report the results of an additional study in Appendix (study 3).

In order to better understand the mechanisms generating the perceived “lack of fit” between prototypical and actual owners, we analyze the participants’ evaluations of the traits of prototypical owners of products. The results of this analysis are presented in Appendix (study 1A).

In sum, in study 1, we find that male-typed products are associated with greater gender price gaps compared to female-typed products: women are penalized more when selling products that are believed to be typically owned by men.

### Study 2: Uncertainty

In study 2, we explore the effects of uncertainty on penalties for female sellers. We predict that buyers rely on gender stereotypes more, and thus penalize female sellers more, when they are more uncertain about the prices or values of products.

One thousand thirty-six participants were randomly assigned to one of two conditions, which varied by whether they evaluated new or used products. They were then presented with a photo of a product that was described as either used or new and were asked questions about it, as described next. Each participant was shown five different products randomly drawn from the larger data set.

Participants were asked how much they would be willing to pay for the product and then to reflect on their decision-making process. They were asked on 7-point scale ranging from *not at all to very much* (1) how certain they were about the price they would be willing to pay, (2) how interested they would be in the prices other people are willing to pay, and (3) how interested they would be in knowing who the current owner is. The three items capture different dimensions of uncertainty regarding the prices of products and the willingness to pay for them. The first item captures the participant’s own uncertainty about his or her willingness to pay for the product. The second item captures the uncertainty about the market price of the product, as reflected in the participant’s eagerness to learn how much others are willing to pay for it. For some products (like money-value gift cards), information about how much others are willing to pay is likely to be almost irrelevant when deciding how much one is willing to pay. For other products, like paintings, information about the prices others are paying is invaluable for learning what the market rate is before deciding how much one is willing to pay. The third item captures the eagerness to learn how much others are willing to pay for it. For some products (like money-value gift cards), information about how much others are willing to pay is likely to be almost irrelevant when deciding how much one is willing to pay.

We aggregated the responses of participants by product and generated variables that represent the average score for each item. As reported in Table 1, participants are moderately uncertain about the price they would be willing to pay ($M = 4.12$), generally quite interested in knowing the price others would pay ($M = 5.12$), and moderately interested in who the owner is ($M = 3.40$). Since the market price should provide more relevant information than the owner’s identity.

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**Table 2. OLS Regression Models Predicting the Female–Male Gap, by Prototypical Owners’ Perceived Sex.**

| Variable                        | Female–Male Price Gap |
|---------------------------------|-----------------------|
| Used                            | .059*                 |
| Likely female owner             | .085**                |
| Used × Likely Female Owner      | −.081*                |
| Price                           | .00004                |
| Constant                        | −.086***              |
| $R^2$                           | .018                  |
| $N$                             | 306                   |

Note: Standard errors in parentheses. OLS = ordinary least squares.

*p < .1. **p < .05. ***p < .01.
it is not surprising that participants are more interested in the price that others would pay.

Results

We predict that people will care more about the identity of the owners of products when they are uncertain about how much they are willing to pay for products or about their market prices. As can be seen in Table 3, in an OLS regression model predicting how interested participants were in knowing who the owner is, a one-unit increase in their uncertainty about how much they are willing to pay for the product increased their interest in who the owner is by 0.23 ($p < .05$, $N = 306$). Likewise, a one-unit increase in people’s uncertainty about the market price of the product—as reflected in their eagerness to learn how much others are willing to pay for the product—increased their interest in who the owner is by 0.46 ($p < .01$, $N = 306$).

Next we show that, as predicted, when people want to know who the owner is, the price gap between women and men increases for new products and decreases for used products. In Model 1 in Table 4, we report the results of an OLS regression model predicting the gender price gap by the interest in who the owner is. We find that a one-unit increase in the interest in who the owner is increases the gender price gap for used products by 0.2 ($p < .12$, $N = 306$). For used products, a one-unit increase in the interest in who the owner is decreases the gender price gap by 0.1 ($0.6 – 0.5; p < .05$, $N = 306$). The results for new products are consistent with our argument that when people are uncertain about the prices of products, they look for clues about the products’ value, such as the identity of the owner. They then rely on this information when deciding how much they are willing to pay. The results for used products are also consistent with the literature on gender stereotypes, which suggests that people tend to view women as more trustworthy than men (Fiske et al. 2002). It is not surprising, therefore, that the gender price gap is smaller for used products.

A second dimension of uncertainty is captured by people’s eagerness to learn how much others are paying for products. In Model 2 in Table 4, we report the results of an OLS regression model predicting the gender price gap by people’s uncertainty about the market prices of products. Similar to the prior dimension of uncertainty, we see that when people are uncertain about the market prices of products—as reflected in their eagerness to learn how much others are paying for them—the price gap between female and male sellers increases for new products and decreases for used products. More precisely, a one-unit increase in the uncertainty about the market price increases the gender price gap for new products by 0.066 ($p < .1$, $N = 306$). In contrast, for used products, a one-unit increase in the uncertainty about the market price decreases the gender price gap by 0.2 ($0.86 – 0.66; p < .01$, $N = 306$). However, in models predicting the gender price gap, the effects of uncertainty about people’s own willingness to pay were statistically insignificant.

When products are used, there is potentially more uncertainty than when products are new, since buyers are uncertain also about the conditions of products. As a result, buyers of used products are more dependent on the descriptions of products that the sellers provide, compared with new products. Buyers of used products may also search for additional clues that would help them assess whether they can trust the

### Table 3. OLS Regression Models Predicting Interest in Who the Owner Is.

| Variable                                      | (1)     | (2)     |
|-----------------------------------------------|---------|---------|
| Uncertain about price                         | 0.229** | (0.097) |
| Used × Uncertain about Price                  | 0.057   | (0.111) |
| Interested in prices others pay               | 0.455***| (0.102) |
| Used × Interested in Prices Others Pay        | −0.022  | (0.113) |
| Used                                          | −0.254  | (0.466) |
| Price                                         | 0.002***| (0.000) |
| Constant                                      | 2.237***| (0.407) |
| $R^2$                                         | 0.262   | 0.363   |
| N                                             | 306     | 306     |

Note: Standard errors in parentheses. OLS = ordinary least squares.

$p < .1$. **$p < .05$. ***$p < .01$.

### Table 4. OLS Regression Models Predicting the Female–Male Gap by Uncertainty.

| Variable                                      | (1)     | (2)     |
|-----------------------------------------------|---------|---------|
| Interested in who the owner is               | −0.049† | (0.031) |
| Used × Interested in Who the Owner Is         | 0.064*  | (0.035) |
| Interested in prices others pay               | −0.066* | (0.034) |
| Used × Interested in Prices Others Pay        | 0.086** | (0.037) |
| Used                                          | −0.202* | (0.120) |
| Price                                         | 0.0007  | (0.0008) |
| Constant                                      | 0.124   | 0.283*  |
| $R^2$                                         | 0.013   | 0.020   |
| N                                             | 306     | 306     |

Note: Standard errors in parentheses. OLS = ordinary least squares.

†$p < .12$. *$p < .1$. **$p < .05$. ***$p < .01$. 
seller and the description. Studies suggest that women are stereotypically viewed as more trustworthy than men (Fiske et al. 2002). Recall also that in the eBay study, it was shown that women were ranked by buyers as better at describing the items they are selling than men (Kricheli-Katz and Regev 2016). It is not surprising, therefore, that with used products, gender price gaps tend to be smaller compared with new products.

**Summary and Discussion**

In this project, we explore why female sellers receive lower prices than male sellers when selling the exact same products and why for some products gender price gaps are larger than others. We make four main contributions. First, we show that people hold gendered cultural beliefs not only about social groups but also about prototypical owners of products and perhaps even about products themselves, stereotyping a drill and a Disney movie and not just their sellers. Second, we show that these cultural beliefs result in gendered price differences of products. Third, we demonstrate that when uncertain about their willingness to pay for a product or about its market price, buyers rely more on their gendered cultural beliefs. Finally, this study makes a methodological contribution by using a series of surveys to uncover the mechanisms behind the empirical findings derived from “big data.”

We start by showing that the gender price gap is affected by whether products are male typed or female typed: when products are believed to be typically owned by men, the price gap between female and male sellers increases. Thus, for example, the price gap between women and men is larger when they sell drills, which are believed to be typically owned by men, as compared to sewing machines, which are believed to be typically owned by women. However, this does not mean that women consistently receive higher prices than men do for products typically owned by women. Instead, the main effect for being a male seller is large enough to overcome the benefit of being a woman selling products typically owned by women.

Then, we present evidence that suggests that people care more about the identity of the owners of products when they are uncertain about how much they are willing to pay for products or about their market prices. We show that when people are uncertain about the market prices of products or about how much they are willing to pay for them, the price gap between female and male sellers increases for new products and decreases for used products. We argue that for new products, it is cultural beliefs about the lower competence of women that increase the gender price gap, and for used products, it is cultural beliefs about the high trustworthiness of women that decreases the gender price gap.

Our findings suggest that cultural beliefs about what women and men are and about what women and men should be play an important role in generating price differences in product markets. We show that women experience similar disadvantages in product markets as they do in labor markets and that similar mechanisms generate these disadvantages. With product markets, and especially with new products, results are particularly informative because products are identical, so quality-related explanations for the gender price gap become irrelevant. Our findings therefore support arguments that in the labor market, wage differences between women and men are the result of cultural beliefs about gender and not only of differences in merit. Furthermore, the existence of gender price gaps in markets other than the labor market implies that the negative effects of cultural beliefs about gender in economic life are greater than previously understood. Finally, building on Thye’s (2000) value theory of power in exchange relations, our findings also demonstrate how the status characteristics of owners of products (like their gender) interact with the traits of prototypical owners of these products to generate value and inequalities in mixed-motive exchange settings.

Unlike with labor markets, private transactions for the sales of products tend not to be regulated by antidiscrimination law. Nonetheless, an emerging body of literature shows that disparities in markets other than the labor market are significant in magnitude and implications. In one field experiment involving baseball card auctions on eBay, it was shown that cards held by a dark-skinned/African American hand were sold for about 20 percent less than cards held by a light-skinned/Caucasian hand (Ayres, Banaji, and Jolls 2015). In another study, it was shown that nonblack hosts on Airbnb charge approximately 12 percent more than black hosts for the equivalent rental, and rental applications from guests with distinctively African American names are 16 percent less likely to be accepted relative to identical guests with distinctively white names (Edelman and Luca 2014; Edelman, Luca, and Svirsky 2017). One study of the Uber ride-sharing company has found that in some locations, passengers with African American–sounding names were subject to longer waiting times and more frequent cancellations and that drivers took female passengers for longer, more expensive rides (Ge et al. 2016). Thus, there is accumulating evidence that discrimination is prevalent in the every growing online peer-to-peer market economy. This evidence suggests a reconsideration of the appropriateness of legal protection from discrimination in peer-to-peer markets and an evaluation of possible interventions. It follows from our study, for example, that one way to reduce discrimination in online markets is by reducing the uncertainty involved with the product, service, or person offering it. As we show, the more uncertainty involved in a transaction, the more people rely on stereotypes. If we do wish to consider the prohibition of discrimination in online product markets and the regulation of the behaviors of users, the effects on material outcomes and on the dignity and autonomy of users should be taken into account together with the harms.
of discrimination. In addition, the feasibility of enforcement in online peer-to-peer markets, as well as the legal responsibility of market platforms to prevent their users from discriminating, should be examined.

Appendix

Two Additional Studies

Study 1A: Gendered Perceptions of Product Owners. We wish to further explore the lack-of-fit hypothesis. We want to know whether price gaps are greater when there is a lack of fit between the perceived traits of prototypical owners and the gender stereotypes about the actual owner.

For this purpose, we conducted an exploratory factor analysis of the eight items used to evaluate prototypical owner-sellers of products: competent, confident, intelligent, pleasant, sincere, high-status worthy, tolerant, and warm (all on scales of 1 to 7). This analysis revealed that the eight items loaded on two distinct dimensions: competence and warmth (see Table A3). Using the factor weights, we created a competence composite from participants' ratings on a 7-point scale of how competent, confident, intelligent, and high-status worthy they believed the owner to be (alpha = .8737). The warmth composite was similarly constructed from participants' ratings of the following items: pleasant, sincere, tolerant, and warm (alpha = .9274). As can be seen in Table 1, the mean of the competence composite is 4.57 and the mean of the warmth composite is 4.39, meaning that overall, prototypical owners were seen as about equally warm and competent.

Psychologists have shown that people tend to define social groups along the two dimensions of competence and warmth. Whereas women are stereotypically viewed as warmer than men, men are viewed as more competent than women. Our study finds that products' owners are similarly evaluated along these dimensions. Traits that loaded consistently across products on the competence dimension were competence, intelligence, high status, and confidence. Traits that loaded consistently across products on the warmth dimension were warmth, pleasantness, tolerance, and sincerity (see Table A4). This suggests that competence and warmth differentiate prototypical owners of products and perhaps even the products themselves. Further, the standard deviation of these ratings per product was on average about 1.1 on a 7-point scale, indicating a consistency in beliefs about the competence and warmth of the products' owners.

For each product, competence and warmth composites were calculated based on the factor analysis. Figure A2 plots products that received extreme high or low warmth and competence scores in the warmth-competence space. We can see, for example, that owners of a Ping G15 driver golf club are perceived to be highly competent but not very warm, whereas owners of a Susan Boyle CD are perceived to be warm but not competent. Owners of a KitchenAid mixer are perceived to be both warm and competent, whereas owners of an $8 Lowe's gift card are perceived to be not very competent and not very warm.

In Models 1 to 3 in Table A3, we report the results of logistic regression models predicting whether the prototypical owner of the product was perceived to be a woman. Indeed, we find that perceptions of prototypical owners as being warm were correlated with believing the prototypical owners were likely to be women, whereas perceptions of prototypical owners as being competent were correlated with believing the owners were men.

More precisely, the table reports the marginal effects of the prototypical owners' competence and warmth on the tendency to perceive owners as women. Marginal effects can be interpreted as the change in the probability of perceiving the owner to be a woman, given a one-unit change in the warmth or competence variables. A one-unit increase in warmth generated a 0.92 increase in the probability of perceiving the owner of the product to be a woman. On the other hand, a one-unit increase in competence decreased the probability that the owner-seller was perceived to be a woman by 0.5.

Perceptions of competence—but not perceptions of warmth—are correlated with the gender price gap (Table A5). When the prototypical owner is perceived to be competent, the gender price gap increases by 0.087 for new products ($p < .05, N = 306$). The perceived warmth of owners is not correlated with the gender price gap. When the perceived gender, competence, and warmth are all included in the same model (Model 3), only the perceived gender is significant. It should be emphasized, though, that the perceived competence and warmth of sellers are both correlated with the perceived gender of sellers.

In sum, we find that people hold consistent and defined beliefs about the characteristics of prototypical owners of products along the dimensions of competence and warmth. Perceptions of prototypical owners as being warm are correlated with believing the prototypical owners are likely to be women, whereas perceptions of prototypical owners as being competent are correlated with believing the prototypical owners are likely to be men. We further show that price gaps tend to be greater when women—who are stereotypically viewed as less competent than men—are selling products that are perceived to be typically owned by competent owners.

Study 3: Gendered Perceptions of Used Products. When used products are sold, two additional conflicting gender-related mechanisms may operate. First, buyers may believe that female owners are more familiar with products typically owned by women and therefore would be willing to pay more for them compared to when these products are sold by men, especially when they themselves are uncertain about the price or quality of the product. The same pattern would be found for men and products typically owned by...
Men. Second, with used products typically owned by women, buyers may believe that women have more heavily used them compared to men. Therefore buyers would be willing to pay less for them compared to when these products are sold by men, especially when the product is one that tends to wear out (e.g., a hair dryer vs. a painting). The same pattern would be found for products typically owned by men.

**Methodology.** The third survey thus focuses only on used products. Participants are randomly assigned to assess products being sold by a woman or a man and are asked to report their perceptions of the owners’ usage of products and their familiarity with them. The perceived gender differences in usage and familiarity are then used to predict the gender price gap of the used products.

Five hundred nineteen participants were randomly assigned to one of two conditions, which varied by the gender of the owners of used products. They were first presented with a photo of a used product that was described as being sold by either Alison or Brad and then were asked to assess (1) how extensively the owner has used the product on a 7-point scale ranging from *not at all* to *very extensively* and (2) how familiar the owner is with products of this type on a 7-point scale ranging from *not at all* to *very much*. Each participant was shown five different products randomly drawn from the larger data set.

We aggregated the responses of participants by product and generated variables that represent the average score for each item. Then, for each product, we constructed the “familiarity gap,” which captures the gap in the perceived familiarity of female and male owners. The gap was calculated as the difference between the average response for how familiar Alison is with the product and the average response for how familiar Brad is with the product. Similarly, for each product, we constructed the “usage gap,” which captures the gap in the perceived usage of female and male owners of the product. This gap was calculated as the difference between the average response for how extensively Alison has used the product and the average response for how extensively Brad has used the product. As we show in Table 1, on average, participants perceive female owners to be less familiar than male owners with the used products they sell. The difference between the familiarity of female owners and the familiarity of male owners is −0.23 (p < .01). The difference between the extent of the perceived usage by women and the extent of the perceived usage by men is −0.08 and is not statistically significant.

In Table A6, we report the results of OLS regression models predicting the gender price gap for used products by whether the prototypical owner is perceived to be female and by how interested people are in the usage. We see in Model 2 that when the typical owners of used products are perceived to be women, the gender price gap decreases by 0.28 (p < .05, N = 207). However, when the extent of usage of the product is important and the typical owners of used products are perceived to be women, the price gap increases by 0.05 (p < .1, N = 207).

![Figure A1. Kernel density estimate of the “likely female owner” variable.](image)
Figure A2. Social perceptions of warmth and competence of product owners.

Table A1. OLS Regression Models Predicting the Number of Bids and Final Price: eBay Auctions 2009 to 2012.

| Variable               | (1) Bids  | (2) Price | (3) Log Price | (4) Log Price | (5) Log Price | (6) Log Price (Gift Cards) |
|------------------------|-----------|-----------|---------------|---------------|---------------|----------------------------|
| Woman                  | −0.885*** | −4.880*** | −0.054***     | −0.029***     | −0.056***     | −0.068***                  |
|                        | (0.027)   | (0.306)   | (0.002)       | (0.002)       | (0.003)       | (0.016)                    |
| Woman × New            |           |           |               |               |               |                            |
| Woman buyer            |           |           |               |               |               | 0.030***                   |
|                        |           |           |               |               |               | (0.003)                    |
| Card title price       |           |           |               |               |               |                            |
| New                    | 1.198***  | 29.447*** | 0.212***      | 0.265***      | 0.210***      | −0.236                     |
|                        | (0.041)   | (0.470)   | (0.003)       | (0.004)       | (0.005)       | (0.189)                    |
| Percentage positive feedback | 0.013*** | 0.081     | 0.001         | 0.001         | 0.000         | −0.005                     |
|                        | (0.004)   | (0.051)   | (0.000)       | (0.000)       | (0.001)       | (0.003)                    |
| Reputation             | 0.003***  | 0.023***  | −0.000***     | −0.000***     | −0.000***     | −0.000***                  |
|                        | (0.000)   | (0.002)   | (0.000)       | (0.000)       | (0.000)       | (0.000)                    |
| Reputation^2           | −0.000*** | −0.000*** | 0.000***      | 0.000***      | 0.000***      | 0.000***                   |
|                        | (0.000)   | (0.000)   | (0.000)       | (0.000)       | (0.000)       | (0.000)                    |
| Years in eBay          | 0.013***  | 0.248***  | 0.014***      | 0.014***      | 0.013***      | 0.013***                   |
|                        | (0.003)   | (0.039)   | (0.000)       | (0.000)       | (0.000)       | (0.002)                    |

(continued)
Table A1. (continued)

| Variable             | (1) Bids  | (2) Price  | (3) Log Price | (4) Log Price | (5) Log Price | (6) Log Price |
|----------------------|-----------|------------|---------------|---------------|---------------|---------------|
| Start price          | -0.036*** | 0.487***   | 0.002***      | 0.002***      | 0.002***      | 0.001***      |
| (0.000)              | (0.001)   | (0.000)    | (0.000)       | (0.000)       | (0.000)       | (0.000)       |
| Dummy reserve        | 0.446***  | 43.48***   | 0.265***      | 0.265***      | 0.279***      | 0.361***      |
| (0.061)              | (0.702)   | (0.005)    | (0.005)       | (0.008)       | (0.078)       |
| Bold title           | 1.851***  | 36.857***  | 0.155***      | 0.155***      | 0.162***      | 0.020         |
| (0.060)              | (0.687)   | (0.005)    | (0.005)       | (0.007)       | (0.085)       |
| Number of pictures   | 0.367***  | 3.988***   | 0.037***      | 0.037***      | 0.039***      | -0.000        |
| (0.007)              | (0.084)   | (0.001)    | (0.001)       | (0.001)       | (0.026)       |
| Stock photo          | -0.072*   | 1.474***   | 0.016***      | 0.016***      | 0.015***      | 0.029         |
| (0.033)              | (0.380)   | (0.003)    | (0.003)       | (0.004)       | (0.029)       |
| Same state           | -0.110*   | -2.079***  | -0.009*       | -0.008*       | -0.002        | -0.033        |
| (0.046)              | (0.534)   | (0.004)    | (0.004)       | (0.006)       | (0.030)       |
| Constant             | 19.520*** | 186.958*** | 4.819***      | 4.808***      | 3.752***      | 2.545***      |
| (0.532)              | (6.124)   | (0.041)    | (0.041)       | (0.057)       | (0.351)       |
| $R^2$                | 0.354     | 0.703      | 0.742         | 0.743         | 0.737         | 0.637         |
| $N$                  | 615735.000 | 61515.000 | 61515.000     | 61515.000     | 259777.000    | 10979.000     |

Note: All regressions include year, start month, end month, start day, end day, duration, and product fixed effects. OLS = ordinary least squares. *p < .05. **p < .01. ***p < .001.

Table A2. Characteristics of Research Participants (Amazon Mechanical Turk).

| Characteristic     | M       | SD     |
|--------------------|---------|--------|
| Female             | 0.449   | 11.24  |
| Age                | 33.799  |        |
| White              | 0.765   |        |
| African American   | 0.061   |        |
| Hispanic           | 0.048   |        |
| Asian              | 0.091   |        |
| Native American    | 0.008   |        |
| Pacific Islander   | 0.003   |        |
| Other              | 0.024   |        |
| Less than high school | 0.008  |        |
| High school or less | 0.095  |        |
| Some college       | 0.281   |        |
| 2-year college     | 0.102   |        |
| 4-year college +   | 0.514   |        |

Note: N = 2,532.

Table A4. Results from Rotated Factor Analysis.

| Perceived Trait       | Factor 1 (Warmth) | Factor 2 (Competence) | Uniqueness |
|-----------------------|-------------------|-----------------------|------------|
| Competent             | .2818             | .868                  | .168       |
| Confident             | .0323             | .830                  | .310       |
| Intelligent           | .271              | .845                  | .212       |
| Pleasant              | .902              | .213                  | .141       |
| Sincere               | .8513             | .254                  | .211       |
| High status           | .0874             | .840                  | .288       |
| Tolerant              | .8795             | .160                  | .201       |
| Warm                  | .9388             | .045                  | .117       |

Table A5. OLS Regression Models Predicting the Female–Male Gap, by Prototypical Owners’ Perceived Gender, Competence, and Warmth.

| Variable               | (1)       | (2)       | (3)       |
|------------------------|-----------|-----------|-----------|
| Used                   | - .371    | -.086     | -.514     |
| (270)                  | (266)     | (351)     |
| Likely female owner    | .109***   | (.045)    |           |
| Used × Likely Female   | - .100*   | (.054)    |           |
| Owner                  |           |           |           |
| Competence composite   | -.087*    | (.051)    | -.048     |
| (0.53)                 | (0.35)    |           |
| Used × Competence      | .085      | .056      |           |
| Composite              | (0.059)   | (0.063)   |           |
| Warmth composite       | - .031    | -.089     |           |
| (0.050)                | (0.057)   |           |
| Used × Warmth          | .023      | .074      |           |
| Composite              | (0.060)   | (0.070)   |           |

Note: Marginal effects are reported with standard errors in parentheses. *p < .1. **p < .05. ***p < .01.
Table A5. (continued)

| Variable                        | (1)  | (2)  | (3)  |
|---------------------------------|------|------|------|
| Price                           | .00007 | .00003 | .00004 |
|                                 | (.00009) | (.00008) | (.00009) |
| Constant                        | .355 | .094 | .518* |
|                                 | (.233) | (.223) | (.306) |
| $R^2$                           | .012 | .004 | .032 |
| $N$                             | 306  | 306  | 306  |

Note: Standard errors in parentheses. OLS = ordinary least squares.
* $p < .1$. ** $p < .05$. *** $p < .01$.

Table A6. OLS Regression Models Predicting the Female–Male Gap (Used Products).

| Variable                        | (1) | (2) |
|---------------------------------|-----|-----|
| Likely female owner             | .001 | .280** |
|                                 | (.021) | (.139) |
| Likely Female Owner $\times$ Interested in Use | $-0.52^*$ | .026 |
| Interested in use               | .045** | (.012) |
| Price                           | .00004 | -.00003 |
|                                 | (.00006) | (.00007) |
| Constant                        | $-0.25^*$ | $-0.26^*$ |
|                                 | (.012) | (.065) |
| $R^2$                           | .002 | .069 |
| $N$                             | 207  | 207  |

Note: Standard errors in parentheses. OLS = ordinary least squares.
* $p < .1$. ** $p < .05$. *** $p < .01$.

Authors’ Note

Data can be accessed upon request.

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