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Abstract

This research aims to demonstrate that the abundant marketing data that companies are using to explore new business opportunities can be an equally fertile source for uncovering an undesirable social attitude or behavior that may be relevant to firms' business. Companies may benefit from this knowledge when developing innovative new programs that aim to benefit society such as CSR initiatives. In this study, we examine boy-girl gender discrimination in China as manifested in parents' purchase decisions on behalf of their children across different markets. Our study in itself is significant because it is the first large-scale empirical work to clearly verify the phenomenon of boy-girl discrimination, taking advantage of e-commerce data. Specifically, we compare the clothing expenditures on boys versus girls using a rich, household-specific dataset obtained from two online retailers. We found a significant effect of higher expenditure on boys over girls, and the relative expenditure difference grew bigger in less developed areas as compared to metropolitan areas. We found that the patterns of gender inequality vary systematically across different geographic markets and social economic conditions. The relative expenditure difference between boys and girls is closely tied with social-economic conditions, education levels, and birth rates of a district. Managerial and social implications are discussed.

Keywords: gender inequality, boy-girl discrimination, cause-related marketing, one-child policy, e-commerce, corporate social responsibility

1 Introduction

It has been well recognized that business practices and their outcomes reflect the social value of firms as well as consumers. In fact, this is the premise for the growing popularity of cause-related marketing and, in general, the corporate social responsibility (CSR) activities by firms. Companies across the globe implement various CSR initiatives that include corporate philanthropy, community support, equal opportunity hiring, diversified employment, eco-friendly manufacturing and cause-related marketing. Companies understand that CSR is not only an ethical or ideological imperative, but also an economic one (Luo and Bhattacharya 2009); that is, through CSR initiatives companies can project better corporate image and gain customer support through positive word-of-mouth (Castaldo, Perrini, Misani, and Tencati 2009), loyalty and purchase (Brown and Dacin 1997; Luo and Bhattacharya 2006). More importantly, a firm promoting positive social values can be perceived as being a responsible corporate citizen. The question, then, is how to uncover social attitude or behavior that may be relevant to a firm's social endeavor. This research aims to demonstrate the potential social implications gleaned from a firm's own, organically occurring marketing data, which may lead to opportunities for better managerial initiatives such as CSR programs without burdening the firm to collect outside survey or sociological/anthropological data.

The beauty care brand Dove, for example, has been delivering a self-esteem campaign, "The Dove Campaign for Real Beauty", for more than 10 years. The cosmetics brand SK-II is another example. In 2016 it launched the "Change Destiny" and #INeverExpire campaigns in

Asia which aim to inspire women to challenge age-related social pressure[1]. Increasing efforts have been made to empower young girls. The "Like A Girl" campaign by Always sets out to redefine the negative connotation of doing things "like a girl", while Barbie's "Imagine the Possibilities" campaign hopes to have a lasting positive impact on young girls, showing them that they can achieve anything they want in life. These powerful cause-related marketing campaigns not only strike a chord with women and young girls, but also promote a desirable social value that calls for a change in attitude and behavior across the entire society. There are many similar examples today, especially in emerging markets.[2] For companies who aim to reach female consumers, the keen observation of the prevalence of undesirable social values and practices is a prerequisite to the success of such sensational cause-related marketing or CSR campaigns. Our research on using firm's transaction data for social implications would be particularly relevant to these companies.

Specifically, we examine the issue of parental boy-girl discrimination within households – a phenomenon that is often observed anecdotally yet is difficult to verify in a society. We explore girl-boy discrimination as manifested in parents' purchase decisions on behalf of their children because we believe having a better understanding of this societal phenomenon is important for several reasons. First, girl-boy discrimination generates enduring but adverse social impact on societal development and growth (Gilligan, Suitor, Seoyoun, and Pillemer 2013; Suitor et al. 2008). In fact, discrimination against girls can begin as early as the prenatal stage by parental discretionary sex selection before birth. After birth, in many societies boys are observed to get better treatment in nutrition, healthcare, and education opportunities (Barcellos, Carvalho, and Lleras-Muney 2014; Hazarika 2000). This parental differential treatment (PDT) has a

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[1] https://www.prnewswire.com/news-releases/sk-iis-ineverexpire-campaign-inspires-women-to-challenge-age-related-pressure-300639059.html

[2] https://econsultancy.com/blog/67626-17-marketing-campaigns-with-a-positive-message-for-women

long-term ill effect on children's developmental experience that lasts into adulthood. Spears and Bigler (2005), for example, argued that children's perception of themselves, as the target of discrimination is likely to affect their self-esteem, peer relations, academic achievement, occupational goals, and mental and physical well-being. When the practice is pervasive it means that society is eventually affected and could potentially devolve into a female-unfriendly environment that further dampens women's performance (Jensen 2012).

Second, while the importance of boy-girl discrimination is well-recognized by sociologists and economists, documenting and measuring this phenomenon is challenging due to the lack of detailed data. Nobel Prize Laureate Angus Deaton (1989) offers a novel approach to examine boy-girl discrimination within a household by comparing the estimates of expenditure elasticity on adult goods (e.g., alcohol or cigarettes) with respect to the change of family members in a gender group. Nevertheless, expenditure more to feed a boy, for example, is not necessarily an act of son-favoring. Biologically, boys need more calories than girls of the same age.[3] While development economics literature offers strong evidence in different welfare-enhancing outcomes like education and nutrition, our research complements the related literature by directly examining the expenditures on children's nonessential goods – that is, consumption not linked to generating future income (i.e., nutrition or education) or human biology, with transaction data possessed by companies. As far as we know, no studies have yet looked into child gender discrimination from this angle.

Third, scholars in marketing have been noticing firms' questionable discriminatory practice by taking advantage of the knowledge of gender differences in product knowledge, attitude or negotiation skill (i.e., Busse, Israeli, and Zettelmeyer 2016; Chen, Li, and Lai 2014, Chen, Yang and Zhao 2008). This research looks into the gender discrimination from the

[3] https://www.nhlbi.nih.gov/health/educational/wecan/downloads/calreqtips.pdf

opposite angle – discriminatory behavior by consumers instead of firms. This research aims to show evidence of discriminatory behavior across consumer segments; when equipped with this knowledge, firms will be able to launch proper cause-related marketing or CSR campaigns that aim to mitigate this behavior.

The data we utilize in this research comes from two leading online children's clothing retail companies in China. Our data is unique to understand the boy-girl discrimination social phenomena for the following reasons: First, China has been moving along the path of gender equality despite being still far from the ideal stage. The interactive effects of a traditional son-preferred culture, rapid economic growth, and the enforced family-planning policy make China an interesting context for examining child gender equality. It is worth mentioning that China's family-planning policy, which limits the number of children per married couple, coupled with rising household income is giving rise to the so-called "Little Emperor or Empress" syndrome, a term used to describe the phenomenon of Chinese families excessively spoiling their children (Wang and Lin 2009).

Second, as explained earlier, examining parents' expenditure on discretionary consumption for their children is an alternative angle to rigorously understand boy-girl discrimination. Among all possible nonessential goods spent on children, we examined specifically the expenditure on young children's clothing. This category is chosen because: 1) unlike expenditure on education or healthcare, parents' expenditure on children's apparel is not associated with children's survival or future earning power, yet differences in the providing these goods to boys versus girls can still have deep impacts on their well-being; 2) clothing is a necessity regardless of parents' socioeconomic conditions. In fact, it is the No.1 purchased category (25.4%) in the maternal and infant supply industry in China; and, 3) a prevalent perception is that parents spend more on girls than boys for their clothing needs in the absence of son or daughter favoritism as reported in New York City Department of Consumer Fair 2015 report. In a setting where there is no cultural history of gender discrimination, they show parents spend 4% more on clothes and 7% more on toys, respectively, for a daughter than a son. Therefore, parents' expenditure on clothes is probably the most salient indicator of discrimination, if there is a reversed outcome.

Third, the online sales data, as compared to traditional household survey data in gender discrimination research, offer many benefits: 1) accessibility – customer purchases are not constrained by distance or location that normally apply to an offline business; In addition, orders are all shipped to actual addresses, information that is not necessarily easily obtainable from off-line store sales; 2) availability – product displays, payment methods, delivery logistics, and customer service are uniformly presented to all shoppers through the largest Chinese e-commerce platform with no specific groups of customers targeted or excluded.

We estimate the degree of girl-boy discrimination against a set of socioeconomic variables. We find that the likelihood for consumers to spend more on boys' clothing relative to girls is higher among those who live in regions that are economically under-developed, less educated, and with lower birth rates. In other words, rural parents are more likely to show favoritism towards boys as compared to urnam parents. Since expenditure is driven by price and/or quantity, we further show that the relative expenditure gap between boys and girls in less developed areas versus that in bigger cities is mainly driven by the price paid. These findings generate substantial social implications for children's clothing companies, as it provides an evidentiary basis for them to use in designing CSR initiatives to have a positive impact on society by reducing parental boy-girl discrimination.

The rest of this paper is organized as follows. Section 2 encompasses a brief review of our research background regarding boy-girl discrimination. Section 3 describes how we organized the data and operationalized our dependent and controlled variables. Next, we document and discuss the results of our analyses and related robustness checks. Lastly, we present our conclusions and implications, address limitations, and finally suggest areas for future research.

2 Research Background: Gender Discrimination

Economists and management scientists have studied gender inequality in adults, including workforce participation and performance, such as gender gap in wages and salary (Blau and Kahn 1994; Ginther and Hayes 1999; Goldin and Polachek 1987), promotions (McDowell et al. 1999), and job access (Gobillon et al. 2015). Even today in corporate America, "glass ceilings" persist in US boardrooms (Financial Times, October 18^{th}, 2010). One in ten S&P 500 companies have no female directors, and women's participation on boards has barely moved since 2005. Ding et al. (2013) found that male scientists were almost twice as likely as females to serve on the corporate scientific advisory boards (SABs). Patterns held for the economics profession as well. Using data from American Economic Association members, McDowell et al. (1999) suggested the promotion prospects for women were inferior to those of their comparable male colleagues.

For gender discrimination on children and adolescents, evidence from literature has not been as rich. One stream of research is on the consequences of boy-favoring discrimination, while the other is the empirical investigations and findings.

Based on US Census data, Ben-Porath and Welch (1976) found that when parents care about the gender of their children, it affects their fertility rate. In fact, child gender preference might lead to male-female ratio imbalance within a society, which over time had a negative impact on female labor force participation (Angrist 2002). In China, the long-time culture of son preference as a result of labor, ritual, inheritance and old-age security practices, combined with the distorted impact of the government's one-child policy produced what may be the largest gender imbalance in the world (Bulte, Heerink, and Zhang 2011). The International Planned Parenthood Federation also revealed that more than 70% of aborted fetuses were female, citing the abortion of up to 750,000 female fetuses in China in 1999 (Baculinao 2004). As a result, figures from the National Bureau of Statistics showed that, at the end of 2014, the Chinese mainland population held 33.76 million more males than females. The sex ratio in China was 115.88 to 100, compared to the worldwide norm of about 107 to 100. Using a model of fertility choice when parents have access to a sex-selection technology and face a mandated fertility limit, Avraham (2011) found that a couple's first son was worth 1.42 years of income more than a first daughter, and the premium was highest among less-educated mothers and families engaged in agriculture. Needless to say, the imbalance of the male-female ratio caused many social and economic problems in China (Wei and Zhang 2011). *Pre-natal* gender discrimination was not the focus of this study, but these findings demonstrated the grave consequences of pervasive gender discrimination within a society.

On *post-natal* matters, PDT was shown to have a long-lasting impact on a child into adulthood. Studies showed that PDT negatively affected children's relationships with siblings as well as parents continuing into their adulthood (Boll, Ferring, and Filipp 2003; Gilligan et al. 2013). In addition, research suggested that the least-favored children experience lower levels of self-esteem and sense of social responsibility, and higher levels of aggression, depression, and bad behavior as adults (Feinberg, Neiderhiser, Howe, and Hetherington 2001; Suitor et al. 2008).

The expression of PDT takes many forms, including day-to-day parent-child interactions (psychological aspects) to goods parents give their children (physical aspects). As parents tend to regard their children as possessions, children can be viewed as an extension of the self (Derdeyn 1979). From a parent's point of view, giving more (or fewer) material objects to their children is not only a way of conveying how much they care about their children, but is also a way of attempting to bring about desired behaviors in their children. Hence, the PDT of giving goods to children has just as much psychological impact as a parent's words or attitude (Garg and Morduch 1998; Lancaster, Maitra, and Ray 2008).

As for the empirical findings of boy-girl discrimination, previous survey-based papers found some evidence in many emerging countries such as India (Behrman 1988; Lancaster, Maitra, and Ray 2008), Bangladesh (Asadullah and Chaudhury 2009), Mexico (Antman 2011), Ghana (Garg and Morduch 1998), Cote D'Ivoire (Haddad and Hoddinott 1994) and Papua New Guinea (Gibson and Rozelle 2004). In these papers children's consumption was often viewed as an intra-family resource allocation or an inter-generational allocation matter. Early research in this area focused on uneven schooling or healthcare that favored boys, with the notion that favorable expenditure on boys' education and healthcare was viewed as an investment in the family's future income. Children who were expected to be more economically productive in the future would receive a larger share of family resources and had a greater propensity to survive. Several studies found pro-male biases regarding education (Lancaster, Maitra, and Ray 2008), nutrition (Behrman 1988), and healthcare (Garg and Morduch 1998; Morduch and Stern 1997) across various countries. But Asadullah and Chaudhury (2009) found reverse gender gaps in education in Bangladesh. Note, however, these studies were often conducted using small samples (i.e., a handful of villages).

Deaton (1989) proposed a new approach to check for child gender discrimination through intra-household expenditure reallocation, though he failed to find boy-girl discrimination in Cote d'Ivoire and Thailand. Many researchers followed his approach and examined the same issue in different countries. For example, using India panel survey data, Subramaniam (1996) found no gender-differential in the intra-household allocation of resources when controlling for fixed effects of households. Using an experimental approach, Begum, Grossman, and Islam (2014) explored parental attitude towards different gendered children. Results suggested that there was no systematic cultural bias in parental attitudes towards the gender of a child. In China, Gong, van Soest, and Zhang (2005) managed to collect a larger sample of data, including more than 5,000 families from 19 Chinese provinces, and analyzed expenditure patterns in rural China. Regarding the decision on education, they found that boys were more often sent to school, and expenditures on a boy that went to school were larger than that on a school-going girl of the same age. Table 1 summarizes all the related research.

---- Insert Table 1 about here ----

In summary, prior social studies have conclusively found that boy-girl discrimination has long-lasting negative impacts on children and our society's development at large. If this boy-girl discrimination appears to be salient, companies, as good corporate citizens, can and should leverage CSR programs to bring public awareness toward this issue and advocate for solutions to reduce this discrimination in our society. However, among empirical investigations in which researchers have been examining whether boys get more favorable household resource allocations, the conclusion thus far is mixed. As we pointed out earlier, indirect measures through intra-household expenditure reallocation is a novel approach. We would like to offer a clearer and more complete picture of boy-girl gender discrimination by looking at direct consumption measures. In what follows, we described our data, approach, and analyses.

3 Data

According to a recent report, sales of maternal and infant supplies in China reached RMB 637 billion in 2017 with a 27.3% growth rate compared to the sales in 2016.[4] Among all categories in maternal and infant supplies, the children's apparel industry was number one (25.4%), followed by baby toys (14.8%). The children's apparel industry, as reported by the National Bureau of Statistics of China, reached RMB 300 billion (USD 47 billion) in sales volume in 2016 with a 25.3% compound annual growth rate (CAGR). The average expenditure on children's apparel was RMB 350 RMB ($55) per child in 2008, growing sharply to RMB 1,700 ($265) in 2017.

First, we introduced companies A and B, two pure e-commerce children's clothing companies in China as our focal data for research. Though these two companies were two of many in this very low-concentrated market in China,[5] they were ranked as the top brands in the children's apparel category on Taobao (the largest e-commerce platform in China), covering almost all geographic markets in the country. We obtained company A's SKU product-level sales data from September 2011 to August 2012 and company B's data from January 2015 to December 2015. Company A had an annual sales of RMB 250 million (USD 40 million) in 2011, while the figure for company B is RMB 500 million (USD 80 million) in 2015. Per their management, the two companies did not have any offline outlets or offline advertising channels, nor did they differentiate their products, prices, or promotions across different regions.

Company A launched two primary brands, one exclusively for boys and the other for girls. Based on the purchase records, we selected customers who had both girls and boys in their

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4 http://www.zhongbangshuju.com/viewdoc?eid=4248C8491C09A07A

5 The number one company, Balabala, has only 3.1% market share comparing to 12% of US's number one brand, Carters.

household. We used this sample for within-subject comparisons as our data for main analyses.

Company B had a uniform brand for boys and girls, but indicated whether a product was designed for boys or for girls in product names and descriptions. Similarly, we used the data containing customers who purchased both girl and boy clothing for our main analyses. We put the within-subject comparison sample from company A as sample A, and the sample from company B as sample B in below.

Sample A and B were both obtained from the company's enterprise resource planning (ERP) system containing information such as item price, discount, category, and shipping addresses. Shipping address was essential because we matched that with district-level statistics obtained from the National Statistics Bureau of China. The latter included socioeconomic information for every administrative district in China. Hence, our research utilized data from multiple sources that we elaborated in detail in sections 3.1 to 3.3. This study was cross-sectional in nature and at the district/county level since we did not have the socioeconomic information at the household level.

3.1 Sales Data from Sample A and Sample B

We removed records that were identified as institutional purchases (i.e., abnormally large orders) or gifts (i.e., shipping to multiple addresses). Sample A contained 150,948 product-level transactions from 63,685 orders purchased from 43 categories (for boys, or girls, or both) by 50,316 customers during the one-year window. These sales data were from 2,843 counties and districts, roughly 78% of the country. Sample B contained 272,227 product-level transactions from 55,382 orders purchased from 11 categories (for boys, or girls, or both) by 41,158 customers during the one-year window. The complete category list was shown in Appendix A1 These sales data covered 2,480 districts in China. Since the analysis was at the district level, we further aggregated the data. For instance, to compute a customer's total expenditure on girls' clothing, we added up all the expenditure, quantities, and orders across all categories of this customer. The average price paid was around 90 RMB in Sample A and 30 RMB in Sample B. Sample A's price range was the price range that the top children's apparel brands Balabala (92.4 RMB), Gap (104.2 RMB) and Zara (94.9 RMB) operated in China, whereas Sample B's was closer to local affordable brands, according to an industry report[6]. Again, These two samples came from two fairly representative companies targeting at mainstream (both upper and lower) consumers. Summary statistics from the sales data would be discussed in section 4.2.

3.2 Data on Socioeconomic Information

The 2010 Census data from the National Bureau of Statistics of China[7] covered all of the 3,640 districts across the entire country. It included information such as average education level (years), birth rate, male-female ratio, and percentage of fertile women, minorities, and children. We further collected 2016 district-level GDP data from the International Data Group (IDG, a leading data, marketing services and venture capital organization) as a proxy for economic development. However, IDG only provided GDP for 2,533 counties, and we missed data for a few hundred small districts especially in the rural area as compared to the sales data. To control all other systematic differences across regions, we constructed regional dummy variables (West, East, South, and North) and city-level dummy variables (metropolitan cities, other cities, and rural counties). Table 2 contained the descriptive statistics of the socioeconomic variables. The total number of unique districts is 2,866 once we combine samples A and B.

---- Insert Table 2 about here ----

3.3 Other Data Sources and Variables

[6] http://www.100ec.cn/detail--6438314.html
[7] Census data in China is collected every 10 years.

Children's clothing could also be purchased from offline retail outlets. Though there was no reason to speculate that parental attitude would be different when parents shopped online versus offline, the concern about the potential effect of shopping formats should be attenuated. Unfortunately, we did not have information about the distribution of children's apparel stores across the country. Instead, we used the information of offline store locations obtained from Balabala, Gap, and Zara in 2011 to form the proxy and to mitigate the impact of offline children's clothing purchases. These three brands were among the top five children's apparel brands in China.

3.3.1 Survey Results from Offline Competitors and Channel Partners

We conducted a survey of Balabala senior executives as well as 74 leading national channel partners of offline children's apparel brands (including Balabala). Some of these channel partners were publicly listed companies that carried a big variety of brands all across China.

Highlights from the survey were listed as follows:

- An overwhelming majority (85%) responded that there were no systematic differences in marketing strategies for boys vs. girls from the brands as well as the channel partners. Prices between boys clothing and girls clothing were very similar.
- Among all the product categories that channel partners operated in, clothing was mostly purchased online (60%). Infant formula was around 30%.
- About half of the respondents thought there was no discrimination in buying clothes for boys vs girls, but for those who thought there was, 76% responded that discrimination was more likely to happen in rural areas and smaller cities.

3.3.2 E-Commerce Development

Another concern is about the degree of e-commerce penetration and competition across different regions. Shoppers in some areas might be more receptive to e-commerce than others. To control for this potentially compounding factor, we included the E-Commerce Development Index in 2015, a continuous variable created by Alibaba (aEDI)[8] in which they gathered both online-shopping and online-retailing information (including customer expenditure, frequency and vendor density, competitiveness) to define the level of e-commerce development in a given district.

3.4 Dependent Variable

Following Deaton (1989), the dependent variable (DV) was the ratio of boys' clothing expenditures to girls' clothing expenditures. We were primarily interested in how this ratio varied across urban vs. rural areas, and how it varied with the social-economic conditions. We constructed this ratio for each district by computing the aggregate expenditure on boys over the aggregate expenditure on girls in all categories in that district. We found that the average ratio across all districts was 1.86, much higher than the benchmark of 1 (i.e. equal expenditure). We also tried constructing the DVs with respect to *Quantities* (the ratio of boys' clothing total quantities to girls' clothing quantities) and *Number of Orders* (the ratio of boys' clothing number of orders to girls' clothing number of orders) and found consistent patterns (1.53 and 1.19, respectively). The descriptive statistics of those ratios were shown in Table 4.

As a face validity check, we correlated those ratios with some province-level measures on gender equality and women's rights such as female unemployment rate and mortality of girls vs. that of boys, and so on. These measures were collected in 2010 from the National Bureau of Statistics of China. At the province level, again we computed the ratios by first aggregating expenditure across customers in a province, and then taking the ratio of boys over girls. The

[8] http://www.aliresearch.com/html/stopic/aedi/about.html

results were shown in Table 3 for Sample A and Sample B. We found, for example, the ratio (expenditure) was negatively correlated with females with college degree rate (r = -.22 for Sample A and r = -.20 for Sample B) but positively correlated to female unemployment rate (r = .11 for Sample A and r = .15 for Sample B), mostly suggesting right directions for face validity at the macro level to some extent.

---- Insert Table 3 and 4 about here ----

3.5 Independent Variables

Previous research suggested that social-economic conditions might influence gender discrimination. For example, the *Science* paper of Guiso et al. (2008) empirically showed that the gender differences in math scores disappeared in countries with a more gender-equal culture and better economic, political and educational opportunities for women. Jensen (2010) also argued that if the market environment improved, women would be able to develop better capabilities that eventually reduce the performance gap.

Therefore, we sorted independent variables into two groups, socioeconomic characteristics and other controlled variables. Below are the socioeconomic characteristics (the primary interest of this research):

GDP. While income was not reported in the Census, local GDP was used as a proxy for the economic development of the district. When a certain area was more economically developed, we speculate that people would be more likely to be open and progressive, and hence, there was less likelihood of son preference. We used GDP instead of GDP per capita, as the latter one was calculated as GDP over number of household registrations (referred to as "hukou"), and thus often less accurate and less reliable in China[9]. GDP was also highly correlated with whether a district was rural ($-.44^{**}$), and we focused on GDP in the regression analyses.

[9] In that case, migrant population was not included in the denominator.

Average education level. This was the number of years of education on average in a certain district. Similarly, when parents were more educated, they were less likely to be bound by traditional mindsets.

Birth rate. This was defined as the average birth rate of a district as a proxy for how many infants were born in a given district. The One-Child Policy drastically reduced the average fertility rate in urban households from about three in 1970 to just over one by 1982. Gupta and Bhat (1997) showed that one consequence of fertility decline in East Asian countries was the increased manifestation of sex bias, including prenatal gender selection, excessive mortality rate of young girls, and continuous gender discrimination in adulthood. Therefore, we conjectured a negative relationship between birth rate and gender discrimination.

Other control variables. We included the male-female ratio (gender balance in the district), minority percentage (percentage of residents who are minorities), region (geographic location dummy variables), percentage of fertile women (percentage of residents who are female and in their child-bearing years), children percentage (percentage of residents who are children), offline shopping (whether a district has a Balabala, Gap or Zara store), and e-commerce development index defined by Alibaba. The correlation matrix of all continuous variables included in the analyses was shown in Appendix A2.

To summarize, our efforts to collect multi-source, multi-type, and multi-company data allowed us to examine the gender discrimination on a scale that previous research could not achieve. In sections 4, 5, and 6 below, we would present how we used these data and what the results were.

4 Empirical Strategy, Analyses, and Results

We intended to show the relative differences of gender discrimination across different city-tiers (urban vs. rural areas) in section 4.1, and across different socioeconomic conditions in section 4.2.

4.1 Discrimination Across City-tiers

We obtained city level information from the he State Council[10] (whether a district was located in a metropolitan city, other city, or rural county). Using our combined sales data of Sample A and Sample B, we compared discrimination ratios across city levels. We contrasted these parameters within each level of districts. We found that the expenditure ratio in rural counties (2.03) was significantly larger than that in metropolitan cities (1.38) at 95% confidence interval using the Tukey test (ANOVA). Similar patterns held for the ratios using quantities and number of orders. The descriptive statistics were shown in Table 4.

Sample A: In Table 5, we compared the number of items and orders, total expenditure, and average paid price between the boy brand and the girl brand that a given customer bought by using a paired-sample t-test. We found that people, in general, spent more (i.e., more items, more orders, more expenditure, and more expensive products) on boys than on girls.

What's more remarkable was the relative differences in expenditure between boys and girls across city tiers. The expenditure gap grew significantly bigger in smaller cities and in rural areas. Footnote e of Table 5 reported the paid price range: boys (44-189 RMB) and girls (28-184 RMB). Though the company did not intentionally set higher price for boys' clothing, it seemed that the purchasing price for boys were higher than that for girls, especially in non-metropolitan areas.

The data allowed us to statistically test the differences in our DVs among district levels. Using the difference between the boy-brand expenditure and the girl-brand expenditure of

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[10] Metropolitan cities, or first-tier cities, are administrative districts of Beijing, Shanghai, Guangzhou and Shenzhen, whereas rural counties are county-governed districts. Other cities are the rest of city-governed districts in China.

metropolitan cities as the reference group (control group) and given the confidence intervals (CI) derived from the difference-in-difference (DID) Tukey test (ANOVA), we found that the difference between boys and girls in rural counties was significantly larger than that of metropolitan cities across the total quantities, number of orders, and total expenditure[11]. Furthermore, the results indicated that the difference between boys and girls in non-metropolitan cities was significantly larger than that of metropolitan cities across the same parameters[12].

Sample B: In Table 6, we compared the same variables between the boy clothing and the girl clothing that a given customer bought by using a paired-sample t-test. The results indicated that people spent more (i.e., more expenditure and more expensive products) on boys than on girls. We found consistent patterns as in Sample A's data, that the expenditure difference between boys and girls was the largest in rural counties.

Unlike Sample A, Sample B reported larger total quantities and number of orders for girls, yet the difference was much smaller in rural areas[13]. Similar to the price effect in Sample A, paid price range for the boy brand was 18-55RMB, whereas that for the girl brand: 8-48 RMB. However, the paid price difference between boys and girls was larger in rural areas than that in metropolitan areas, resulting in significantly larger relative expenditure difference between boys and girls in rural areas[14]. Buying more expensive clothes for boys, undoubtedly, was a strong

[11] difference_quantity_metropolitan = 1.05; difference_quantity_rural = 1.32 with CI of the DID test = [0.03 to 0.52]; difference_orders_metropolitan = 0.26; difference_orders_rural = 0.43 with CI of the DID test = [0.07 to 0.26]; difference_expenditure_metropolitan = 84.49; difference_expenditure_rural = 115.51 with CI of the DID test = [10.88 to 51.16].

[12] difference_quantity_metropolitan = 1.05; difference_quantity_cities = 1.27 with CI of the DID test = [0.01 to 0.43]; difference_orders_metropolitan = 0.26; difference_orders_cities = 0.39 with CI of the DID test = [0.05 to 0.21]; difference_expenditure_metropolitan = 84.49; difference_expenditure_cities = 106.98 with CI of the DID test = [5.03 to 39.94].

[13] difference_quantity_metropolitan = -0.72; difference_quantity_rural = -0.23 with CI of the DID test = [0.13 to 0.85]; difference_orders_metropolitan = -0.08; difference_orders_rural = -0.05 with CI of the DID test = [0.00 to 0.05].

[14] difference_expenditure_metropolitan = 5.69; difference_expenditure_rural = 20.27 with CI of the DID test = [3.31 to 25.85]).

manifestation of favoritism in rural areas of China.

---- Insert Table 5 and 6 about here ----

Expenditure, by definition, was driven by purchase quantity and price. For quantity difference, one might argue that gender differences in wearing clothes could be the driving factor for the higher expenditure on boys. For example, boys were naturally more active, so they wore out clothes faster and required more purchases than girls did.

However, in today's world where waste from clothing was a global trending topic, actual wear-out of children's clothes rarely happened (more likely to grow out instead). Industry experts and the International Textile Fair Claims Consumer Guide further confirmed that children's clothing was designed to last more than 3 years, and boys' clothes often used more long-lasting fabrics. In fact, Table 6 of Sample B data offered additional support that the expenditure difference was not driven by quantity consumption.

Still, to address the potential issue of wear-out or usage difference, besides running an all-category analysis, we consulted with the vendors, and selected a few subcategories that had similar purchase quantity and frequency rate between boys and girls (such as coat, down coat, vest, hat, and long pants). In other words, these categories were least likely to have different wear-and-tear/usage rates between boys and girls.

As indicated earlier, there were 43 categories in Sample A and only 11 categories in Sample B. Due to the coarseness in category definitions of Sample B, we decided to only use Sample A for the subsample category examination.

The final subsample contained 2,633 customers who had both boys and girls in the household. The results shown in Table 7 revealed that while these subcategories had similar purchase quantity and frequency between boys and girls, the price paid was significantly higher for boys in rural areas (paid price range for boys: 49-266 RMB; for girls: 38-282 RMB).

Then, we performed the DID Tukey test (ANOVA) to understand whether the differences among city levels in price paid and expenditure were significant. We found that the difference between paid average price for boy and paid average price for girl in rural counties was significantly larger than that difference in metropolitan cities[15]. Also, although the difference between expenditure for boy clothing and girl clothing in rural areas was not significantly larger than the difference in metropolitan cities[16], the values of these differences among city levels indicated a consistent pattern that the expenditure gap between boys and girls was the largest in rural areas.

In summary, these three sets of summary statistics in Section 4 showed three scenarios: Table 5: all key measures were higher for boys over girls; Table 6: quantities and frequency were higher for girls, but the price paid was the opposite; and Table 7: quantities and frequency were not significantly different, but the price paid was higher for boys. In all three scenarios, we found consistent evidence that the paid price difference between boys and girls in rural counties was larger than the expenditure difference in metropolitan cities. Suce price difference was the key driver of expenditure gap in gender in rural counties, contrary to previous media reports in the US (New York City Department of Consumer Fair 2015 report) and UK (Daily Mail Sep 11th, 2016) that girls should have higher expenditure on clothing.

---- Insert Table 7 about here ----

4.2 Discrimination Associated with Socioeconomic Variables

The OLS was the primary estimation method we employed in this study after testing on homoscedasticity. Results from the combined sample (district-level) were shown in Table 8. The

[15] difference_price_metropolitan = -0.95; difference_price_rural = 12.54 with CI of the DID test = [4.64 to 22.34]

[16] difference_expenditure_metropolitan = -0.69; difference_expenditure_rural = 28.67 with CI of the DID test = [-6.00 to 64.72]

results revealed that families in more economically advanced areas ($B = -.16$, $p < .05$), in districts with higher education level ($B = -.09$, $p < .05$), and in the areas with higher birth rates ($B = -.04$, $p < .05$) were less discriminatory towards their girls. Similar patterns held when using *Quantity* and *Number of Orders* as the DVs. All these results were aligned with our conjectures. Appendix A3 contained the full results of our main regression analyses. To ensure the validity and reliability of our analyses, we conducted a series of robustness checks, shown in section 5.

---- Insert Table 8 about here ----

5 Robustness Checks

Our measures were potentially subject to confounding factors that might not truly reflect gender discrimination. Hence, we first provided a discussion of our empirical strategies to address these concerns in section 5.1. The details of the robustness checks discussed in section 5.1 are then reported in sections 5.2-5.7.

5.1 Discussion on Potential Confounding Factors

In this section, we listed potential confounding factors to our gender discrimination measure and explained how we would try to rule out them. First, one might argue that consumer brand preference could potentially confound our measure. For example, even though the company did not deliberately implement gender-specific marketing strategies, the boy brand might be better received by rural customers, while the girl brand might be better received by city customers. To rule out this, we conducted Robustness Check 1, in which we used customer-level analysis in rural counties only, combining both samples. The patterns of discrimination across socioeconomic conditions still held in this more homogeneous subsample.

Second, though wear-out was not the key discussion focus, we would like to further demonstrate our empirical robustness in this vein. We selected consumers who at least purchased one product category twice during the one-year time window of our analyses with a size increase and aggregated these customers' purchases to district level. These customers' purchases were more likely to reflect the fact that children had outgrown rather than worn out the clothes. Using this sub-sample, we re-ran our main regression analysis in Robustness Check 2. Unfortunately, clothing size information was only available to us in Sample A but not in Sample B. Thus, we only implemented this robustness check using Sample A and we were able to replicate our results.

Third, to eliminate the concern that districts with few customer representatives might bias the obtained results, we re-ran our main regression analysis using data with the bottom 10%, 20%, and 30% samples trimmed accordingly (based on the number of customers aggregated to a district). The consistent results we gained in Robustness Check 3 helped enhance the reliability of our findings.

Fourth, although the company executives mentioned that they didn't implement any district-specific marketing strategy, it was possible that the availability of offline options and competitive landscape in each region was different. While we tried our best to control for offline competitions, one may question: 1) As compared to the boys, whether urban girls had more options than rural girls in the offline space and therefore, clothing for urban girls was bought offline (substitution effect); and 2) As compared to the boys, whether urban girls could return more easily than rural girls (return effect). For the first case, intuitively, as compared to boys, urban girls would have more variety, more expensive options, and more try-on opportunities than rural girls in the offline space, meaning that the relative urban girls/urban boys' online consumption should not be higher than their rural counterparts, but we observed that in our results. Therefore, considering the possibility of offline options, our results would be even more strengthened. For the return argument, unfortunately we did not have return information in this dataset. However, China is probably one of the most advanced countries in logistics covering rural areas with speedy delivery and flexible return policy. A working paper on online product returns (Zhang et al. 2019) used data from a leading women's clothing company and found no systematic differences between urban return rates and rural return rates.

To further control for the unobserved local demand and supply factors that might muddle our results, we performed Robustness Check 4, which proposed an incremental measure of gender discrimination, i.e., the relative favoritism towards boy in families with both boy and girl comparing to the favoritism to boy vs. girl among families with children of the single gender in the same location. This comparison controlled for unobserved local demand and supply factors. We found even stronger evidence of gender discrimination in families with children of mixed genders.

Next, the inherent family composition and birth order might also affect the relative expenditure on boy vs. girl. From the sampling perspective, the distribution of BG (boy-then-girl) family and GB (girl-then-boy) family might be unbalanced[17]. Then if there was favoritism towards younger or older kid, this might confound our results on gender discrimination. Thus, we implemented Robustness Check 5, which compared the expenditure ratios of the second child vs. the first child in the GB family versus the in GG family, and versus the BG family, and further confirmed that the favoritism was indeed towards the boy instead of the younger kid. Again, we computed the ratios by first aggregating across households and then taking the ratio of the second child over the first one. We used the clothing size as a proxy for child age to determine if a family is a BG, GB, or GG family. Although size was probably not a

[17] See Appendix A4 for the detail composition of family types across city tiers.

clean proxy for age, we could use size as a screening variable for two-children families, which we defined as families who purchased clothes that were more than two sizes apart within the year of study. For instance, if a family purchased a boy clothing with a size bigger than a boy clothing's size by 2 sizes, this family is deemed as BB family. Again this robustness check only used Sample A as only Sample A has clothing size information.

Lastly, given that China was a big country with substantial climate variation across regions, one might concern that popular items purchased could be different across regions (e.g. coat vs. T-shirt). In order to better control for demand across categories and across regions, we conducted Robustness Check 6, which computed average gender discrimination ratio for each category for each region.

5.2 Robustness Check 1: Samples from Rural Counties Only

China was a unique market where rural areas had an extraordinarily high mobile Internet penetration rate of 84.6% in 2014, with 84.4% of rural residents liked to shop online and spent RMB 2,000 (USD 300) on average in 2014[18]. Families in rural counties might rely more on the Internet shopping to purchase children's clothing because physical children's apparel stores in rural areas were less accessible and convenient. Of course street bazaar in villages was a common offline option, but its selection was not comparable to the online offerings. One may wonder if rural families might happen to like the boy brand more, and/or the street bazaars for obtaining girls' clothes were relatively easier.

To address this concern, we applied the same analysis at the customer level in rural counties, and the results from this subsample (combined Samples A and B with a sample size of 9,933 customers) were shown in Table 9. Again, when using expenditure as the dependent variable, we found that families from more educated areas were less likely to be discriminatory

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[18] https://www.forbes.com/sites/ceibs/2014/11/10/mobile-and-rural-dual-engines-for-alibabas-future/

toward girls (B = -.16, $p < .05$), and the same for the districts with higher birth rates (B = -.04, $p < .05$). Though only for this particular robustness check, results were not significant using the incremental measure for *Quantity* and *Number of Orders,* the signs were consistent with our predictions. Like what we found in summary statistics in Table 5, 6, and 7 and as we discussed before, we believed that the expenditure gap in rural counties was mainly driven by relative paid price difference between boys and girls (i.e. rural parents tended to buy more expensive clothes for boys than for girls), not quantity. The analysis here further confirmed our previous finding.

---- Insert Table 9 about here ----

5.3 Robustness Check 2: Eliminating Wear Out Concern: Main Regression Analysis from Sample A

Here we utilized one additional variable we had from Sample A: Size. Sizes across different clothing categories could be very sparse. For example, a child may need size 120 for t-shirt, but size 130 for outwear. Children usually grow (at least) one size up every year, with boys and girls following very similar growth chart patterns. Also, this sample was the BG/GB sample, and the two-child BB or GG sample would not be an issue. We selected customers who at least purchased a certain category twice or more with a size increase during the time window of our data (one year). Our assumption was that these customers purchased these products of the same category because their kids outgrew those products, rather than because those produces were worn out. In fact, we could imagine that if the products got worn out easily, customers (especially rural customers) would not want to purchase the brand again.

We aggregated these customer-level data into district level and re-ran our main regression analysis. These customers were from 1,567 districts. The results with expenditure as the dependent variable presented in Table 10 suggested that families in more economically advanced areas (B = -1.17, $p < .05$) and in districts with higher education level (B = -.55, $p < .05$) were less discriminatory towards their girl children. Although we did not find a statistically significant relationship between birth rate and ratio of gender discrimination (B = -.15 $p > .05$), the direction of the coefficient was the same as the previous analysis. We also found consistent results when we used quantity and number of orders as the dependent variables, shown in Table 10. These largely consistent results further suggested that wear-out issue was not a major concern of our research.

---- Insert Table 10 about here ----

5.4 Robustness Check 3: Removing Bottom Districts with Fewer Customer Representatives

We tried to address the concern that some districts with few customer representatives may bias the obtained results. The average number of households in each district was about 20, with 2% of the districts having more than 100 customers, and 30% of the districts having fewer than 10 customers. Thus, we trimmed our data by removing the bottom 10%, 20%, and 30% samples based on the number of customers aggregated to a district, and then ran the main regression analysis three times, one for each subsample. The results were shown in Table 11 with all three ratios of gender discrimination (expenditure, quantity, and number of orders) as the dependent variables, as we did in the main regression analysis (shown in Table 8). The completely aligned results we obtained in Table 11 and Table 8 helped enhance the reliability of our findings.

---- Insert Table 11 about here ----

5.5 Robustness Check 4: Incremental Measure of Gender Discrimination Controlling Unobserved Local Factors

We constructed an additional and incremental gender discrimination ratio, with the nominator being the expenditure for boys from the hetero-gender children families (families with both boys and girls), over the expenditure for boys from boy-only families; and the denominator being the expenditure for girls from the hetero-gender children families over the expenditure for girls from girl-only families. We also created similar measures for quantity and number orders following the above operationalization. In that way, we got a cleaner and tighter measure of the incremental gender effect in hetero-gender family over same-gender children family while controlling for unobserved local factors.

Note that the new measure could also be written as [(the expenditure for boys from hetero-gender children families) / (the expenditure for girls from hetero-gender children families)]*[(the expenditure for girls from girl-only family/the expenditure for boys from boy-only families)], which also equals to our previous DV weighted by the inverse of expenditure ratio from same-gender families. Same applied to the quantity and number of orders measures.

As shown in Table 12, the overall ratio (expenditure) for Sample A was 2.67 and that for Sample B was 2.17. Metropolitan cities, other cities, and rural counties are 1.71, 2.12, and 3.34 respectively for Sample A; and 1.51, 1.95, and 2.54 respectively for Sample B. The new measure seemed to suggest that stronger evidence of discrimination, as the ratio was even higher in hetero-gender family when we control for other factors. More importantly, the correlation between the new measure and the original one is also significant and positive (Sample A: .83; Sample B: .94). We also found similar patterns for quantity and number of orders, shown in Table 12. All the summary statistics of our incremental measures suggested good validity.

Once we combined Samples A and B, we performed the district-level analyses again and found gender discrimination was negatively correlated with economic development (B = -.19, p

< .05), as shown in Table 13. We were unable to replicate the results for education and birth rate this time; however, their signs were consistent with our main results. Similar patterns were found when using quantity and number of orders as the dependent variable, shown in Table 13. Overall, we felt the incremental measure provided additional robustness to the main regression analyses.

---- Insert Table 12 and 13 about here ----

5.6 Robustness Check 5: Gender Discrimination Vs. Birth Order Favoritism

In order to address the birth order concern, what is the impact of having a second child on the firstborn? Some might argue that it is the favoritism towards the younger child (or older child) rather than towards the boy.

Using size as a screening variable for two-children families, we were left with 887 districts for the GG vs. GB comparison, and 723 districts for the GB vs. BG comparison. Note that the GB families in the two sets of samples were slightly different, as the number of BG families was smaller than that of GG families.

There were also possibilities of sharing or pass-on of gender-neutral clothing between siblings of different gender. However, given the inherent nature of boy-girl families (that girls were born first, and mostly in rural counties where we observed higher expenditure for boys), we assumed that parents were less likely to purchase girl clothes intentionally for their younger sons to wear later.

We compared the ratio in Expenditure, Quantity, and Number of Orders of the second-born over the first-born in the above three sets of families at the district level. As shown in Table 14, the paired-sample t-tests were all significant. The ratios of expenditure for the second born vs. first born in the GB family were larger than those in the GG family and those in the BG family, indicating a stronger level of favoritism towards the boys regardless of the birth order. In spite of the potential pass-on in the GG families, all the robustness checks so far consistently suggested compelling evidence that there was stronger favoritism towards boys.

---- Insert Table 14 about here ----

5.7 Robustness Check 6: Demand Across Regions

Given the wide landscape of China, certain product categories might be purchased differently across regions. The concern here was whether there were regional demand side factors that drove the differences in category popularity in rural areas vs. urban areas. For example, expensive coats might be more popular in the north, whereas cheap t-shirts might ne more popular in the south.

However, what truly matters should be the relative gender difference in expenditure in rural cities as compared to that in metropolitan cities. In addition to include regional dummies in the main regression analysis, we conducted an additional robustness check to further control for demand difference in rural cities vs. metropolitan cities across regions (North, South, East, and West).

Using customer-level data, we split the sample based on a district's region and whether it was a metropolitan city. For example, Beijing, as a metropolitan city, would be compared with the regional average of the North; Shanghai with the East; Guangzhou and Shenzhen with the South. Then, we calculated the average expenditure, quantity, and order ratio for boy clothing and girl clothing, and took the gender discrimination ratios. As shown in Table 15, regardless of regions, gender discrimination ratios were consistently lower in metropolitan cities as compared to their regional average. The relative difference in metropolitan cities versus the rest of the region seemed to be largest in the South, where enjoyed mostly warm weather. In fact, in Beijing, a northern, cold, and largest city in China, we observed the opposite effect in Sample B: parents were spending more on girls than on boys.

---- Insert Table 15 about here ----

6 Additional Analysis: Implications from the One-Child Policy in Policy-Restricted Areas vs. Non-Restricted Areas

The one-child policy was imposed across China from late 1970s to 2015; however, there were a few exceptions. Four areas in Mainland China (i.e., rural counties in Chengde, Jiuquan, Linfen, and Enshi) and two special administrative regions, Hong Kong (HK) and Macau, were not subject to the one-child policy. Specifically, for the four areas in Mainland China selected by the Chinese State Family Planning Commission, regardless of the first child's gender, families could bear a second child, called the two-child policy. As to the special administrative regions, families did not have any restrictions on the number of children they could have. For our analysis, we also added Taiwan (TW) to the latter group (no restrictions), which also enjoyed a higher level of economic development as compared to most parts of Mainland China. We anticipated lower ratios of child gender discrimination in the non-restricted regions than the policy-restricted areas. In fact, we contrasted the ratios for these three types of regions (shown in Table 16), combining both Samples A and B and found the expected results: The ratios of boy-girl discrimination (*Expenditure*) in the non-restricted areas were significantly lower than the policy-restricted areas ($\text{Mean}_{\text{policy-restricted areas}} = 2.17$, $\text{Mean}_{\text{non-policy-restricted areas in mainland}} = 1.08$, t-value = 8.40, $\text{Mean}_{\text{hk,macau,tw}} = 1.41$, t-value = 3.16). Similar results were revealed when *Quantity* and *Number of orders* were tested. Thus, we concluded that the one-child policy (low birth rate) is a salient factor associated with gender discrimination.

---- Insert Table 16 about here ----

With these analyses and robustness checks, we were convinced that boy-girl discrimination still existed in China during that data time period, and the degree of gender bias varied across socioeconomic factors. Our results, complementing to Guiso et al. (2008)'s finding, showed that better economic conditions, better education, and higher birth rates were some of the factors that diminished boy-girl discrimination in consumption.

7 Discussion and Conclusion

Discrimination against girls is universally regarded as socially unacceptable and yet, it is still very prevalent worldwide. As stated in a recent NGO report, thirty percent of countries are characterized by discrimination against girls (55 of 185 countries).[19] Sociologists worry that pervasive girl discrimination within households could potentially transcend to a female-unfriendly society and create further gender frictions in the workplace. Business communities certainly cannot ignore this threat as they have been working hard to promote and comply with gender-equal work environments.

The actual acts of discrimination against girls are, unfortunately, hard to detect because they are done behind closed doors and unobservable to outsiders. Also, as Deaton (1989) mentioned, the ability to detect boy-girl child discrimination is hampered by a lack of data on actual intra-household resource allocations. Hence, our study in itself is significant because it is the first large-scale empirical work to clearly show the phenomenon of boy-girl discrimination, taking advantage of e-commerce data.

On boy-girl discrimination, there was a paragraph cited in an ancient Chinese book, *Book of Songs* (1000-700 B.C.):

> "When a son is born,
> Let him sleep on the bed,
> Wrap him with fine clothes,
> And give him jade to play...
> When a daughter is born,
> Let her sleep on the ground,
> Clothe her in plain swaddle,
> And give her cotton spinning wheel to play..."

[19] www.savethechildren.org

In ancient times, Chinese boys were treated so much better than girls as soon as they were born. Thousands of years later, we found Chinese parents treating their girls much better, though families living in rural China still acted like their ancestors. Fortunately, our study showed that the degree of discrimination diminishes as economic development, community openness and the level of education increase. In other words, as socioeconomic conditions of a society continue to improve, discrimination will likely gradually subside and hopefully disappear altogether.

In summary, we found:

- Families in economically less-developed areas and rural areas were more likely to show boy-girl discrimination tendency compared to those living in more prosperous cities.
- The expenditure difference was largely due to the fact that rural parents were more likely to choose higher-priced items for boys than for girls their peers in urban areas.
- Higher education and birth rate could reduce this discrimination.
- The newly less-restricted population-control policy is expected to reduce the degree of discrimination, if it can indeed promote higher birth rates.

Our analysis of marketing data related to e-commerce purchases of children's clothing revealed the existence of the undesirable social behavior of parental discrimination against girls, particularly in less developed rural areas of China. This may have practical implications for companies looking to design corporate initiatives such as CSR programs that can help educate the public and mitigate this problem.

Like their western counterparts, many Chinese companies are now aware of the importance of CSR as the Chinese government is also putting pressure on businesses and society to comply with responsible and ethical business policies. Between 2010 and 2018 China dropped from 61st (among 134 countries) to 103rd (among 149 countries) in the World Economic Forum's Gender Gap Report[20]. Economic disparities between the sexes tend to narrow as countries grow richer (*Economist*, May 18th 2019 issue). To market in these rapid-developing emerging markets, companies should seek opportunities to carry out cause-related marketing or CSR initiatives to educate families about the importance and benefits of treating children of both genders equally. China's geographically widespread provinces and regions display cultural differences while sharing some cultural roots. Combining these local cultural variations with the different organizational cultures of companies, it is understandable that the notion of CSR in China faces more challenges; companies probably need to embrace a tailored approach based on the interface of three dimensions: customer segmentation, regional idiosyncrasy, and economic development – as illustrated by our study.

Echoing the recommendation made by the #SaveTheChirdren report, our results suggest that companies should 1) invest in achieving gender equality, including increasing expenditure and monitoring budgets designed to close gender gaps, especially those living in rural, marginalized, vulnerable populations. For example, launching initiatives for girls to access to basic services and empowerment programs. #UnitedbyHalf, is a campaign promoting gender equality in India, the second largest market for United Colors of Benetton. The company's long-term Benetton Women Empowerment Program quickly opens its previously male customer-targeted brand to female consumers; 2) raise awareness in advertising campaigns. The gender equality issue was a key theme Cannes Lions Festival for several years, with theme being not objectifying women and girls portrayed in advertising, and increasing women in the higher echelons of the greater advertising and marketing workplace. For example, Cannes Glass Lion Award winner, Whisper's "Touch a Pickle" Sanitary Napkins campaign, aims to break

[20] https://www.livescience.com/18573-countries-gender-equality-ranking.html

menstruation rules of “not touching a pickle” in India. According to AdAge, more than 2.9 million women pledged to “touch the pickle jar” after seeing the ad, and Whisper’s share of voice grew from 21 percent to 91 percent in its category.

In summary, the contribution of this study is twofold. First, as noted in marketing communities, the strategy of customer segmenting and targeting, which has worked well for exploring new business opportunities, can be equally useful when developing innovative CSR campaigns. Our study demonstrates that today’s abundant marketing data obtained by companies through online and mobile e-commerce and other activities can be a fertile source for uncovering social causes that would otherwise remain subtle or hidden. Second, on the issue of discrimination against girls, though it is universally considered unacceptable, it is difficult to document let alone to verify its presence. This study is the first to investigate the phenomenon on a large scale and statistically substantiate its existence in the China context and with China-focused data.

There are a few caveats to address. Boy-girl discrimination is a complex issue. Discretionary parental actions on behalf of their children are motivated by both self-interest and altruistic reasons. What we discovered in the children’s clothing category is just a piece of corroborating evidence for such acts. Ideally, other discretionary expenditure categories, children’s toys or books, for example, should be examined concurrently. Unfortunately, these data are not readily accessible to the authors. Furthermore, though the purchase data we examined is at the unit of households, we do not have household-specific data. To take advantage of the statistics gathered from the Chinese Bureau of Statistics, data was aggregated, and analyses were carried out at the district level. Thus, based on our findings, we cannot infer or suggest any possible reasons or motives for parental boy-girl discrimination on nonessential expenditures. Thirdly, though we tried our best to control for offline options, obtaining complete information on competitive landscape is always a challenge in many studies. One future research direction is to model and analyze the behavior at the household level provided that household-specific information is available or can be properly inferred through other measurable proxies.

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Table 1

Empirical Studies on Boy-girl Discrimination

Reference	Country	Dependent Variable	Findings
Antman (2011)	Mexico	Intra-household resource allocation	Immigration of the head of the household affects resource allocation for boys vs. girls.
Asadullah and Chaudhury (2009)	Bangladesh	Education expenditure	Reverse gender gap is significant.
Begum, Grossman, and Islam (2014)	Bangladesh	Parental attitudes towards children	No cultural bias in gender is found.
Behrman (1988)	India	Intra-household resource allocation of nutrients	Significant son bias is revealed.
Ben-Porath and Welch (1976)	US and Bengali	Sex preference	Sex preference influences fertility.
Ben-Porath and Welch (1976)	India	Intra-household resource allocation	No significant findings regarding sex preference are found.
Bhalotra and Attfield (1998)	Pakistan	Intra-household resource allocation	Little evidence on gender differences among children is found.
Deaton (1989)	Cote D'lvoire and Thailand	Intra-household resource allocation	No evidence on gender differences among children is found.
Garg and Morduch (1998)	Ghana	Health expenditure among siblings	Significant son bias is revealed.
Gibson (1997)	Papua New Guinea	Household expenditure	Pro-male bias on expenditure is found.
Gibson and Rozelle (2004)	Papua New Guinea	Intra-household resource allocation	Son bias is more prominent in rural areas but less prominent in regions of matrilineal descent.
Gong et al. (2005)	Rural China	Intra-household resource allocation	No gender differentials are found in food and alcohol expenditure but significant son bias is revealed in education expenditure.
Haddad and Hoddinott (1994)	Cote D'lvoire	Children's anthropometric status	Increases in the proportion of cash income accruing to women can increase boys' height-for-age relative to girls.
Haddad and Reardon (1993)	Burkina Faso	Intra-household resource allocation	No evidence on son bias is found.
Lancaster, Maitra, and Ray (2008)	India	Education expenditure	Son bias reveals significant impact on education.
Li (2007)	China	Sex ratio at birth	Discrimination against girls has been demonstrated in both pre-natal and post-natal periods.
Morduch and Stern (1997)	Bangladesh	Health treatment	Significant son bias is revealed.
Song (2008)	China	Intra-household resource allocation	Gender discrimination is found during the early age of children.
Subramaniam (1996)	India	Intra-household resource allocation	No evidence on gender differences among children is found.
Zimmermann (2012)	India	Education expenditure	Children's age has a positive impact on discrimination against girls.

Table 2

Descriptive Statistics of Part Two Data (Number of Unique Districts)

Variable	Percentage
Region	
North	35.80%
South	28.58%
West	9.63%
East	25.99%
City Level	
Metropolitan cities	2.06%
Other cities	50.56%
Rural counties	47.38%

Variable	N	Mean	Std. Deviation	Minimum	Maximum
Log (GDP)	2533	0.89	0.90	-2.33	4.01
Average education (Years)	2866	9.01	1.32	2.42	13.11
Birth rate	2866	10.26%	3.60%	1.79%	25.24%
Male female ratio	2866	1.05	0.06	0.73	1.57
Percentage of minority	2866	11.99%	23.86%	0.00%	98.92%
Percentage of children	2866	16.47%	4.98%	1.05%	35.93%
Percentage of fertile women	2866	28.45%	2.37%	21.33%	38.67%
E-commerce index	2866	12.08	3.95	2.91	52.59

N = 2,866 except for log (GDP) which is 2,533.

Table 3

Face Validity Check of Gender Discrimination Ratios

		Female employment rate	**Female unemployment rate**	**Female professional rate**	**Female NPC[a] member rate**	**Mortality of girls vs. that of boys**	**Female with no education rate**	**Female with college degree rate**
Sample A	Ratio of Gender Discrimination (*Expenditure*)	-0.05	0.11	-0.04	-0.30	0.42	0.19	-0.22
	Ratio of Gender Discrimination (*Quantity*)	-0.09	0.06	0.01	-0.26	0.21	-0.02	-0.18
	Ratio of Gender Discrimination (*Order*)	-0.26	-0.03	0.11	-0.26	0.06	-0.17	-0.03
	Alternative Gender Discrimination Ratio (*Expenditure*)	0.12	0.11	-0.00	-0.22	0.24	0.23	-0.07
Sample B	Ratio of Gender Discrimination (*Expenditure*)	0.14	0.15	-0.12	-0.11	0.05	-0.14	-0.20
	Ratio of Gender Discrimination (*Quantity*)	0.21	0.18	-0.07	-0.20	0.22	0.60	-0.24
	Ratio of Gender Discrimination (*Order*)	0.07	0.14	0.04	0.12	-0.06	0.14	-0.31
	Alternative Gender Discrimination Ratio (*Expenditure*)	0.17	0.08	-0.10	-0.05	0.08	-0.09	-0.20

N=31 Pearson correlation
a: the National People's Congress

Table 4

Descriptive Statistics of Various Operationalization of Gender Discrimination (Combined Samples A and B)

				95% Confidence Interval[b]	
Operationalization	**City Level**	**Mean**	**Std. Deviation**	**Lower**	**Upper**
Ratio of gender discrimination (*Expenditure* on boys' clothing vs. *Expenditure* on girls' clothing)	Metropolitan Cities	1.38[a]	0.82		
	Other Cities	1.72	1.69	-0.23	0.92
	Rural counties	2.03	3.33	0.08	1.23
	Total	**1.86**	**2.60**		
Ratio of gender discrimination (*Quantity* of boys' clothing vs. *Quantity* of girls' clothing)	Metropolitan Cities	1.20[a]	0.57		
	Other Cities	1.43	1.05	-0.09	0.55
	Rural counties	1.65	1.79	0.13	0.77
	Total	**1.53**	**1.45**		
Ratio of gender discrimination (Number of *orders* for boys' clothing vs. Number of *orders* for girls' clothing)	Metropolitan Cities	1.10[a]	0.23		
	Other Cities	1.17	0.49	-0.04	0.19
	Rural counties	1.21	0.59	-0.01	0.23
	Total	**1.19**	**0.53**		

a. The ratio of metropolitan cities was the reference group.
b. The total number of districts or sample size used for main regression analyses was 5,323, which was the sum of the number of districts in Sample A and Sample B.
c. We implemented a Tukey test (ANOVA) to examine whether the differences among city levels were statistically significant at a 95% confidence interval.
N = 5,323.

Table 5

Sample A Data (All Categories): Customers Who Bought from Both Boy Brand and Girl Brand: Expenditure on Boy Brand vs. Expenditure on Girl Brand

	Item Quantities (Total)				95% Confidence Interval[d]		Number of Orders				95% Confidence Interval[d]		Total Expenditure				95% Confidence Interval[d]	
City Level	Boy	Girl	t-value[b]	D[c]	Lower	Upper	Boy	Girl	t-value[b]	D[c]	Lower	Upper	Boy	Girl	t-value[b]	D[c]	Lower	Upper
Metropolitan Cities	3.59	2.54	13.50*	1.05[a]			1.71	1.45	9.86*	0.26[a]			279.22	194.73	14.06*	84.49[a]		
Other Cities	3.86	2.59	38.16*	1.27	0.01	0.43	1.92	1.53	31.04*	0.39	0.05	0.21	315.80	208.82	38.87*	106.98	5.03	39.94
Rural counties	3.75	2.43	22.59*	1.32	0.03	0.52	1.93	1.50	18.88*	0.43	0.07	0.26	320.90	205.39	23.05*	115.51	10.88	51.16

	Paid Average Price[d]				95% Confidence Interval[d]	
City Level	Boy	Girl	t-value[b]	D[c]	Lower	Upper
Metropolitan Cities	84.40	81.25	3.46*	3.15[a]		
Other Cities	87.74	85.32	6.92*	2.42	-3.01	1.55
Rural counties	91.74	89.54	3.26*	2.21	-3.57	1.69

a. Difference between boy-brand expenditure and girl-brand expenditure of people in metropolitan cities was the reference group.
b. T-value was derived from paired samples t-test between boy brand and girl band. *. $p < 0.05$ one-tail test. N = 50,316.
c. D was short for difference between boy-brand expenditure and girl-brand expenditure.
d. Difference-in-differences (DID) significant test was used to examine if the differences were significantly distinct among city levels with the difference in metropolitan cities (i.e., 1.05 for item quantities) as the reference. We implemented a Tukey test in post-hoc tests. There was a significant difference in differences if the confidence intervals derived from the DID Tukey test did not contain zero.
e. Paid price range (10th percentile – 90th percentile to avoid extreme values) for boy brand:44-189(RMB); Paid price range (10th percentile – 90th percentile to avoid extreme values) for girl brand: 28-184 (RMB)

Table 6

Sample B Data (All Categories): Customers Who Bought Both Boy Clothing and Girl Clothing: Expenditure on Boy Clothing vs. Expenditure on Girl Clothing

	Item Quantities (Total)				**95% Confidence Interval[d]**		**Number of Orders**				**95% Confidence Interval[d]**		**Total Expenditure**				**95% Confidence Interval[d]**	
City Level	Boy	Girl	t-value[b]	D[c]	Lower	Upper	Boy	Girl	t-value[b]	D[c]	Lower	Upper	Boy	Girl	t-value[b]	D[c]	Lower	Upper
Metropolitan Cities	3.28	4.01	-8.86*	-0.72[a]			1.12	1.19	-9.40*	-0.08[a]			102.79	97.11	2.33*	5.69[a]		
Other Cities	3.26	3.64	-6.02*	-0.38	0.04	0.64	1.12	1.18	-14.78*	-0.05	0.00	0.04	109.98	94.39	7.72*	15.59	0.41	19.39
Rural counties	3.34	3.57	-3.08*	-0.23	0.13	0.85	1.10	1.15	-9.27*	-0.05	0.00	0.05	113.81	93.54	9.37*	20.27	3.31	25.85

	Paid Average Price[e]				**95% Confidence Interval[d]**	
City Level	Boy	Girl	t-value[b]	D[c]	Lower	Upper
Metropolitan Cities	32.77	25.04	19.74*	7.73[a]		
Other Cities	34.96	28.34	19.41*	6.63	-2.83	0.62
Rural counties	36.09	28.81	12.14*	7.28	-2.49	1.60

a. Difference between boy clothing expenditure and girl clothing expenditure of people in metropolitan cities was the reference group.
b. T-value was derived from paired samples t-test between boy brand and girl band. *. $p < 0.05$ one-tail test. N = 41,158.
c. D was short for difference between boy clothing expenditure and girl clothing expenditure.
d. Difference-in-differences (DID) significant test was used to examine if the differences were significantly distinct among city levels with the difference in metropolitan cities (i.e., -0.72 for item quantities) as the reference group. We implemented a Tukey test in post-hoc tests. There was a significant difference in differences if the confidence intervals derived from the DID Tukey test did not contain zero.
e. Paid price range （10th percentile – 90th percentile to avoid extreme values）for boy clothing:18-55(RMB); Paid price range (10th percentile – 90th percentile to avoid extreme values) for girl clothing: 8-48 (RMB)

Table 7

Sample A (Sub-categories - coat, down coat, hat, and long pants): Customers Who Bought Both from Boy Brand and Girl Brand: Expenditure on Boy Brand vs. Expenditure on Girl Brand

City Level	Item Quantities (Total)				95% Confidence Interval[d]		Number of Orders				95% Confidence Interval[d]		Total Expenditure				95% Confidence Interval[d]	
	Boy	Girl	t-value[b]	D[c]	Lower	Upper	Boy	Girl	t-value[b]	D[c]	Lower	Upper	Boy	Girl	t-value[b]	D[c]	Lower	Upper
Metropolitan Cities	1.29	1.28	0.24	0.01[a]			1.10	1.07	1.38	0.03[a]			237.65	238.33	-0.05	-0.69[a]		
Other Cities	1.36	1.34	1.03	0.02	-0.13	0.15	1.14	1.14	0.17	0.00	-0.11	0.04	241.17	235.95	1.06	5.22	-24.77	36.59
Rural counties	1.42	1.37	0.99	0.05	-0.13	0.20	1.14	1.14	0.09	0.00	-0.12	0.05	268.15	239.47	2.66*	28.67	-6.00	64.72

City Level	Paid Average Price[e]				95% Confidence Interval[d]	
	Boy	Girl	t-value[b]	D[c]	Lower	Upper
Metropolitan Cities	179.13	180.08	-0.29	-0.95		
Other Cities	175.56	175.08	0.38	0.47	-6.26	9.10
Rural counties	185.62	173.08	4.77*	12.54	4.64	22.34

a. Difference between boy-brand expenditure and girl-brand expenditure of people in metropolitan cities was the reference group.
b. T-value was derived from paired samples t-test between boy brand and girl band. *. $p < 0.05$ one-tail test. N = 2,633
c. D was short for difference between boy-brand expenditure and girl-brand expenditure.
d. Difference-in-differences (DID) significant test was used to examine if the differences were significantly distinct among city levels with the difference in metropolitan cities (i.e., 0.01 for item quantities) as the reference group. We implemented a Tukey test in post-hoc tests. There was a significant difference in differences if the confidence intervals derived from the DID Tukey test did not contain zero.
e. Paid price range (10^{th} percentile – 90^{th} percentile to avoid extreme values) for boy brand:49-266 (RMB); Paid price range (10^{th} percentile – 90^{th} percentile to avoid extreme values) for girl brand: 38-282(RMB)

Table 8

OLS Results for Main Regression Analyses (Combined Samples A and B)

	Main regression analysis with ratio of gender discrimination (*Expenditure*) as DV (District-level data)		**Main regression analysis** with ratio of gender discrimination (*Quantity*) as DV (District-level data)		**Main regression analysis** with ratio of gender discrimination (O*rders*) as DV (District-level data)	
	Within-subject (families with both boys and girls) comparison: expenditure on boys' clothing vs. expenditure on girls' clothing					
Variables	**B**	**t-value**	**B**	**t-value**	**B**	**t-value**
Log (GDP)	-0.16*	-4.48	-0.10*	-4.13	-0.03*	-2.58
Average education (Years）	-0.09*	-3.03	-0.05*	-2.11	-0.02*	-1.75
Birth rate	-0.04*	-3.30	-0.02*	-2.89	-0.01*	-2.19
Sample[a]	0.55*	13.14	0.78*	25.71	0.40*	32.04
Covariates[b]						
R-Square	6.20%		13.27%		17.31%	

* p < .05. N = 4,816, the reduced sample size was because we were unable to obtain some small counties' GDP information.

a: Sample B as the reference group.

b. Covariates consisted of cities levels (other cities and rural cities with metropolitan cities as the reference group), male-female ratio, percentage of minority, region, offline shopping (Balala Children Clothing Company), e-commerce development index, percentage of fertile women, and percentage of children.

Table 9

OLS Results for Robustness Check 1 - Customers from Rural Counties (Combined Samples A and B)

	Robustness Check 1 with ratio of gender discrimination (*Expenditure*) as DV (Customer-level data[b] - rural counties only)		**Robustness Check 1** with ratio of gender discrimination (*Quantity*) as DV (Customer-level data[b] - rural counties only)		**Robustness Check 1** with ratio of gender discrimination (*Order*) as DV (Customer-level data[b] - rural counties only)	
	Within-subject (families with both boys and girls) comparison: expenditure on boys' clothing vs. expenditure on girls' clothing		Within-subject (families with both boys and girls) comparison: quantity of boys' clothing vs. quantity of girls' clothing		Within-subject (families with both boys and girls) comparison: orders of boys' clothing vs. orders of girls' clothing	
Variables	**B**	**t-value**	**B**	**t-value**	**B**	**t-value**
Log (GDP)	0.03	0.49	-0.03	-0.85	-0.01	-0.84
Average education (Years）	-0.16*	-2.06	-0.04	-1.01	-0.01	-0.67
Birth rate	-0.04*	-2.44	-0.01	-1.05	-0.01	-1.50
Sample[a]	1.05	10.17	0.34	5.71	0.12	5.78
Covariates[b]						
R-Square	7.23%		14.25%		19.53%	

* p < .05. N = 18,210

a. Sample B as the reference group.

b. Covariates consisted of male-female ratio, percentage of minority, region, offline shopping (Balala Children Clothing Company), e-commerce development index, percentage of fertile women, and percentage of children. In this analysis, since it was the customer level data, we also included promotion intensity, number of orders, average product quantity per order, and average order price as covariates.

Table 10

Robustness Check 2 – Eliminating Wear Out Concern (Sample A) – OLS Results

	Robustness Check 2 with ratio of gender discrimination (*Expenditure*) as DV (District-level data)		**Robustness Check 2** with ratio of gender discrimination (*Quantity*) as DV (District-level data)		**Robustness Check 2** with ratio of gender discrimination (*Orders*) as DV (District-level data)	
	Within-subject (families with both boys and girls) comparison: expenditure on boys' clothing vs. expenditure on girls' clothing. Also, these families have purchased a certain category at least twice with size increases.		Within-subject (families with both boys and girls) comparison: quantity of boys' clothing vs. quantity of girls' clothing. Also, these families have purchased a certain category at least twice with size increases.		Within-subject (families with both boys and girls) comparison: orders of boys' clothing vs. orders of girls' clothing. Also, these families have purchased a certain category at least twice with size increases.	
Variables	**B**	**t-value**	**B**	**t-value**	**B**	**t-value**
Log (GDP)	-1.17*	-3.99	-0.61*	-4.34	-0.22*	-3.47
Average education (Years）	-0.55*	-2.45	-0.19	-1.59	-0.11*	-2.11
Birth rate	-0.15	-1.47	-0.05	-1.06	-0.03	-1.23
Covariates[a]						
R-Square	6.37%		5.64%		4.93%	

* $p < .05$. N = 1,567

a. Covariates consisted of cities levels (other cities and rural cities with metropolitan cities as the reference group), male-female ratio, percentage of minority, region, offline shopping (Balala Children Clothing Company), e-commerce development index, percentage of fertile women, and percentage of children.

Table 11

Robustness Check 3: OLS Results for Main Regression Analyses (Combined Samples A and B)- Removed Bottom 10%, 20%, and 30% Districts with Fewer Customer Representatives.

	Main regression analysis with ratio of gender discrimination (*Expenditure*) as DV (District-level data)		**Main regression analysis** with ratio of gender discrimination (*Quantity*) as DV (District-level data)		**Main regression analysis** with ratio of gender discrimination (O*rders*) as DV (District-level data)	
	Within-subject (families with both boys and girls) comparison: expenditure on boys' clothing vs. expenditure on girls' clothing					
Variables (Bottom 10% removed: N = 4,415)	**B**	**t-value**	**B**	**t-value**	**B**	**t-value**
Log (GDP)	-0.16*	-4.89	-0.11*	-4.57	-0.03*	-3.19
Average education (Years）	-0.11*	-3.97	-0.08*	-3.55	-0.02*	-2.64
Birth rate	-0.04*	-3.68	-0.02*	-2.79	-0.01*	-1.94
Sample[a]	0.48*	11.96	0.77*	25.48	0.41*	32.02
Covariates[b]						
R-Square	6.10%		14.53%		19.32%	
Variables (Bottom 20% removed: N = 4,045)	**B**	**t-value**	**B**	**t-value**	**B**	**t-value**
Log (GDP)	-0.16*	-4.95	-0.11*	-4.50	-0.03*	-3.31
Average education (Years）	-0.10*	-3.74	-0.07*	-3.42	-0.03*	-3.23
Birth rate	-0.04*	-3.46	-0.03*	-3.10	-0.01*	-2.38
Sample[a]	0.46*	12.00	0.76	26.10	0.40	31.29
Covariates[b]						
R-Square	6.60%		16.71%		20.98%	
Variables (Bottom 30% removed: N = 3,712)	**B**	**t-value**	**B**	**t-value**	**B**	**t-value**
Log (GDP)	-0.12*	-3.90	-0.08*	-3.41	-0.03*	-2.90
Average education (Years）	-0.08*	-3.08	-0.06*	-3.23	-0.03*	-3.12
Birth rate	-0.03*	-3.27	-0.03*	-3.55	-0.01*	-3.08
Sample[a]	0.41*	11.46	0.72	26.80	0.39	31.09
Covariates[b]						
R-Square	6.04%		18.37%		22.76%	

* p < .05.

a: Sample B as the reference group.

b. Covariates consisted of cities levels (other cities and rural cities with metropolitan cities as the reference group), male-female ratio, percentage of minority, region, offline shopping (Balala Children Clothing Company), e-commerce development index, percentage of fertile women, and percentage of children.

Table 12

Robustness Check 4 – Eliminating Local Confounding Factors —Descriptive Statistics of Incremental Gender Discrimination Ratio

					95% Confidence Interval of the Difference	
Operationalization	**City Level**	**Mean**	**Difference**	**t-value[c]**	**Lower**	**Upper**
Company A: Alternative Gender Discrimination Ratio (*Expenditure*)[a]	Metropolitan Cities	1.71[b]				
	Other Cities	2.12	0.41	2.85	0.13	0.70
	Rural counties	3.34	1.63	4.91	0.98	2.29
	Total	**2.67**				
Company A: Alternative Gender Discrimination Ratio (*Quantity*)[a]	Metropolitan Cities	1.59[b]				
	Other Cities	1.74	0.15	1.41	-0.06	0.35
	Rural counties	2.03	0.44	3.75	0.21	0.68
	Total	**1.87**				
Company A: Alternative Gender Discrimination Ratio (*Order*)[a]	Metropolitan Cities	1.26[b]				
	Other Cities	1.29	0.03	0.95	-0.04	0.11
	Rural counties	1.35	0.09	2.31	0.01	0.17
	Total	**1.32**				
Company A[d]: Correlations between alternative operationalization and original ratio of gender discrimination (*Expenditure*)				.83**		
Company A[d]: Correlations between alternative operationalization and original ratio of gender discrimination (*Quantity*)				.57**		
Company A[d]: Correlations between alternative operationalization and original ratio of gender discrimination (*Order*)				.89**		
Company B: Alternative Gender Discrimination Ratio (*Expenditure*)[a]	Metropolitan Cities	1.51[b]				
	Other Cities	1.95	0.44	3.00	0.15	0.73
	Rural counties	2.54	1.03	3.49	0.45	1.61
	Total	**2.17**				
Company B: Alternative Gender Discrimination Ratio (*Quantity*)[a]	Metropolitan Cities	1.43[b]				
	Other Cities	1.82	0.39	3.60	0.18	0.60
	Rural counties	2.20	0.77	5.37	0.49	1.05
	Total	**2.05**				
Company B: Alternative Gender Discrimination Ratio (*Order*)[a]	Metropolitan Cities	0.99[b]				
	Other Cities	1.01	0.02	0.89	-0.02	0.05
	Rural counties	1.02	0.03	1.42	-0.01	0.06
	Total	**1.02**				
Company B[e]: Correlations between alternative operationalization and original ratio of gender discrimination (*Expenditure*)				.94**		
Company B[e]: Correlations between alternative operationalization and original ratio of gender discrimination (*Quantity*)				.88**		
Company B[e]: Correlations between alternative operationalization and original ratio of gender discrimination (*Order*)				.92**		

a: The operationalization: (expenditure or quantity or number of orders for boys from families with both boys and girls /expenditure or quantity or number of orders for boys from boy only families) / (expenditure or quantity or number of orders for girls from families with both boys and girls/expenditure or quantity or number of orders for girls from girls only families). We aggregated the data to district-level.
b: The ratio of metropolitan cities was the reference group.
c: Two-tail test. Independent samples t-test. The tests did not assume equal variances
d: Company A sample = 2,562. ** Correlation was significant at the 0.01 level (two-tailed).
e: Company B sample = 2,479. ** Correlation was significant at the 0.01 level (two-tailed).

Table 13
Robustness Check 4 – Eliminating Local Confounding Factors — OLS Results (Combined Samples A and B) Using Incremental Gender Discrimination Ratio

	The alternative operationalization as DV -*Expenditure* (District-level data)		The alternative operationalization as DV -*Quantity* (District-level data)		The alternative operationalization as DV -*Order* (District-level data)	
Variables	**B**	**t-value**	**B**	**t-value**	**B**	**t-value**
Log (GDP)	-0.19*	-4.47	-0.17*	-4.59	-0.02*	-2.33
Average education (Years）	-0.06	-1.46	-0.02	-0.55	-0.02*	-2.78
Birth rate	-0.01	-0.42	-0.00	-0.17	-0.01*	-2.87
Sample[a]	0.25*	4.32	-0.02	-0.36	0.29*	23.70
Covariates[b]						
R-Square	2.50%		1.43%		12.49%	

N = 4,418 (Sample size reduced from 5,041 to 4,418 because that we included log (GDP) in the model and we were unable to retrieve information on GDP for some cities.)
* p < .05.
a. Sample B as the reference group.
b. Covariates consisted of cities levels (other cities and rural cities with metropolitan cities as the reference group), male-female ratio, percentage of minority, region, offline shopping (Balala Children Clothing Company), e-commerce development index, percentage of fertile women, and percentage of children.

Table 14
Robustness Check 5 (Sample A) : Gender Discrimination Vs. Birth Order Favoritism: Ratio Comparisons[a] for second born vs. first born between Girl-girl (GG) Families[b] and Girl-boy (GB) Families[b], and between GB Families and Boy-girl (BG) Families[b]

Gender Discrimination Ratio	GB Families	GG Families	Mean Difference	t-value	95% Confidence Interval Lower	95% Confidence Interval Upper
Expenditure[c]	1.57	1.09	0.48	6.47	0.34	0.63
Quantity[c]	1.54	1.11	0.43	7.87	0.33	0.54
Order[c]	1.55	1.10	0.45	8.04	0.34	0.56
Gender Discrimination Ratio	**GB Families**	**BG Families**	**Mean Difference**	**t-value**	**95% Confidence Interval Lower**	**95% Confidence Interval Upper**
Expenditure[c]	1.59	1.04	0.55	6.44	0.38	0.71
Quantity[c]	1.56	1.12	0.44	6.25	0.30	0.57
Order[c]	1.56	1.04	0.52	8.27	0.40	0.64

a: We first aggregated the ratio of expenditure between the second born vs. first born for GG families, GB families, and BG families to district level, and then conducted two paired-samples t-tests using this district-level data. One to compare GB families and GG families (N=887), and the other to compare GB families and BG families (N = 723).

b: GG families were those with the first born child being a girl and the second born child being a girl as well. GB families were those with the first born child being a girl, and the second born child being a boy. BG families were those with the first born child being a boy and the second born child being a girl.

c: Expenditure of GB families: expenditure for boy (the second born)/expenditure for girl (the first born); Expenditure of GG families: expenditure for girl (the second born)/expenditure for girl (the first born); Expenditure of BG families: expenditure for girl (the second born)/expenditure for boy (the first born); Quantity of GB families: quantity purchased for boy (the second born)/ quantity purchased for girl (the first born); Quantity of GG families: quantity purchased for girl (the second born)/ quantity purchased for girl (the first born); Quantity of BG families: quantity purchased for girl (the second born)/ quantity purchased for boy (the first born); Order of GB families: orders purchased for boy (the second born)/ orders purchased for girl (the first born); Order of GG families: orders purchased for girl (the second born)/ orders purchased for girl (the first born); Order of BG families: orders purchased for girl (the second born)/ orders purchased for boy (the first born).

Table 15

Gender Discrimination Ratios by Regions and by Metropolitan Cities[a] –Sample A and B

Sample	**North (excluding Beijing)**			***Beijing***			**South (excluding Guangdong and Shenzhen)**			***Guangzhou***			***Shenzhen***		
	Expenditure	Quantity	Orders	Expenditure	Quantity	Orders	Expenditure	Quantity	Orders	Expenditure	Quantity	Orders	Expenditure	Quantity	Orders
Sample A	1.97	1.75	1.33	1.93	1.57	1.21	1.91	1.34	1.10	1.66	1.47	1.18	1.79	1.52	1.20
Sample B	1.11	0.86	0.96	0.97	0.76	0.93	1.11	0.84	0.95	1.02	0.78	0.95	1.11	0.90	0.93

Sample	**East (excluding Shanghai)**			***Shanghai***			**West**		
	Expenditure	Quantity	Orders	Expenditure	Quantity	Orders	Expenditure	Quantity	Orders
Sample A	1.74	1.57	1.25	1.70	1.48	1.20	1.76	1.61	1.25
Sample B	1.19	0.92	0.96	1.08	0.85	0.93	1.31	0.98	0.95

a: Using customer-level data, we split the sample based on a district's region and whether it was a metropolitan city. Then, we calculated the average expenditure, quantity, and order for boy clothing and girl clothing, and took the gender discrimination ratios across the above segments using the calculated averages.

Table 16

Additional Analysis: Ratio of Gender Discrimination Between Policy-Restricted Areas and Non-Policy-Restricted Areas (Combined Samples A and B)

					95% Confidence Interval of the Difference	
	City Level	**Mean**	**Difference**	**t-value**	**Lower**	**Upper**
Ratio of Gender Discrimination (*Expenditure*)	Policy-Restricted Areas	2.17[a]				
	Non-Policy-Restricted Areas in Mainland China[b]	1.08	1.10	8.40	0.84	1.36
	HK, Macau, and TW	1.41	0.77	3.16	0.27	1.27
Ratio of Gender Discrimination (*Quantity*)	Policy-Restricted Areas	1.49[a]				
	Non-Policy-Restricted Areas in Mainland China[b]	1.04	0.45	3.68	0.20	0.69
	HK, Macau, and TW	1.04	0.45	2.26	0.04	0.87
Ratio of Gender Discrimination (*Order*)	Policy-Restricted Areas	1.15[a]				
	Non-Policy-Restricted Areas in Mainland China[b]	1.03	0.12	2.39	0.02	0.22
	HK, Macau, and TW	0.99	0.16	3.70	0.07	0.25

Two-tail test. Independent samples t-test. The tests did not assume equal variances.
a: Policy-restricted areas were the reference group.
b: Non-policy-restricted areas in mainland china included Chengde, Jiuquan, Linfen, and Enshi.