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Measuring the Effectiveness of Salespeople: Evidence from a Cold-Drink Market

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Abstract

Salespeople are widely employed in many industries and are perceived as an effective marketing strategy. However, due to lack of field data, direct empirical evidence on the effectiveness of salespeople is scarce. In this paper, leveraging a unique retail sales data set from a leading Chinese cold-drink manufacturer and information on its implemented salespeople assignment rule, we measure the causal effect of salespeople on product revenue. Our estimation strategy features a non-linear control function approach to address the endogeneity problem in salespeople assignment by exploiting the manufacturer's internal allocation rules. Our results show that the marginal effect of the first salesperson is 16.2 percent and that of the second is 10.6 percent. We provide some evidence on the incentive issues caused by the manufacturer's compensation plan as a possible explanation for the decreasing effect of an additional salesperson.

Topics: Labour markets; Service sector
JEL codes: L81, M3, M5

1 Introduction

Salespeople are widely employed in many industries. Zoltners, Sinha and Lorimer (2008) conservatively estimate that US companies spend $800 billion on salespeople each year, close to three times the amount spent on advertising. However, due to lack of field data, direct empirical evidence on the effectiveness of salespeople is scarce.[1]

The key obstacle in establishing the causal effect of salespeople on product sales is that the salespeople assignment is endogenously determined by firms so that it depends on unobserved factors that affect product sales. For instance, firms tend to allocate more sales force efforts in territories with greater potential sales. Failure to account for the endogeneity problem in the sales force size can potentially bias the estimated effects (Albers, Mantrala and Sridhar 2010, Misra 2019). Although this endogeneity problem has long been recognized, few studies have handled it satisfactorily due to lack of information on the decision process of salespeople assignment.[2] The object of the current paper is to fill this gap in the literature.

We obtain transaction data from a leading cold drinks manufacturer in China. The data consists of detailed information on sales of the manufacturer's products in six major supermarket chains in Southeast China from 2018 to 2019. Also, the manufacturer provides data on its salespeople (locations, wages, etc.) working in these chains during the same period. By matching product sales data with salesperson information, we try to estimate the causal effect of salespeople on revenue.

We address the endogeneity problem by exploiting the salespeople assignment rule implemented by the manufacturer. Basically, the rule can be described by two monthly wholesale revenue (MWR) thresholds, namely, T and $3T$, where T is a money amount that cannot be revealed due to confidentiality. For stores with previous MWR that is lower than T, the manufacturer assigns no salesperson to the store; for a store with previous MWR that is higher than T but lower than $3T$, the manufacturer assigns one salesperson to the store; for a store with previous MWR that is higher than $3T$, the manufacturer assigns two salespeople to the store. Empirically, we find that assigning the first salesperson follows the above rule (based on short-term performance) more closely than assigning the second one, which suggests that the manufacturer's decision on the latter is based more on long-term considerations.

Leveraging the information on the assignment rule, we employ a non-linear control function (NCF) approach to address the endogeneity problem.[3] The results show that assigning one salesperson increases revenue by about 16.2 percent, while assigning an ad-

[1]Exceptions include Gatignon and Hanssens (1987), Manchanda, Rossi and Chintagunta (2004), Mizik and Jacobson (2004), Narayanan, Desiraju and Chintagunta (2004) and Jain, Misra and Rudi (2020), among others. We shall provide a detailed literature review later.

[2]For details, see excellent reviews by Albers, Mantrala and Sridhar (2010), Mantrala et al. (2010) and Albers, Raman and Lee (2015).

[3]The above rule may not be strictly followed in reality due to adjustment costs. Our estimation strategy respects this fact by allowing for "errors" in the assignment rule. We will come back to this point later.

ditional one further increases revenue by about 10.6 percent, indicating that the marginal effect of salespeople decreases with the sales force size. To illustrate the economic significance of our estimated effects, we conduct a simple benefit-cost analysis by computing the ratios of the revenue generated by salespeople to their total salaries. The result shows that, on average, salespeople generate revenue approximately four times their costs.

Note that by properly controlling for the endogeneity problem of the sales force size, our results are substantially different from those obtained by regressions that simply control for lagged terms or store fixed effects. Hence, our paper highlights the usefulness of exploiting the firm's decision-making process to help measure the effectiveness of marketing strategies.

The decreasing marginal benefit of an additional salesperson may be driven by incentive problems caused by the manufacturer's compensation plan. According to the compensation plan, each of the two salespeople gets only 75 percent of the commission based on the revenue when they work together, rather than 100 percent when they work independently. Therefore, although store revenue will be higher with two salespeople than with only one salesperson, a salesperson who works with another salesperson is likely to receive a lower commission than one who works independently. We empirically test this hypothesis and find that salespeople who work with a colleague get 19 percent less commission than those who work independently. For salespeople, the decrease in marginal return from making efforts can reduce their incentives to make efforts. The decline in incentives to make efforts is also reflected in the decline in attendance rate: our analysis shows that salespeople would work approximately one day less per month when an additional salesperson is assigned to the store.

Our study contributes to the sales force literature in several ways. First, we empirically measure the effectiveness of salespeople in a context of supermarket retailing using field data. Second, we contribute to the literature by revealing some details about the salespeople assignment rules, which, to the best of our knowledge, is rarely documented in previous studies. Third, combining the first and second points, we address the endogeneity issue in the sales force size by employing an NCF approach.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data and the salespeople assignment rule implemented by the manufacturer. Section 4 conducts empirical analysis. Section 5 concludes.

2 Related literature

Our work contributes to the literature on measuring the effectiveness of salespeople. Besides some early theoretical discussions (Basu et al. 1985, Wernerfelt 1994), most empirical studies focus on the pharmaceutical industry (Mizik and Jacobson 2004, Narayanan, Desiraju and Chintagunta 2004, Manchanda, Rossi and Chintagunta 2004, Chintagunta, Jiang and Jin 2009, Ching and Ishihara 2010, 2012, Shapiro 2018, Huang, Shum and

Tan 2019). Our paper is among the first empirical studies on the effectiveness of salespeople in a retail market. Moreover, with a few exceptions (e.g., Mizik and Jacobson (2004), Manchanda, Rossi and Chintagunta (2004), Narayanan, Desiraju and Chintagunta (2004) and Jain, Misra and Rudi (2020), among others), most existing studies pay limited attention to the endogeneity issue of the sales force size, and therefore potentially get biased estimates of the effectiveness of salespeople.

Mizik and Jacobson (2004) investigate the long-term effect of detailing on prescriptions and address the endogeneity problem by controlling for physician fixed effects and using lagged terms as instruments. They find the effect of detailing on prescriptions is statistically significant but economically modest. Huang, Shum and Tan (2019) also mitigate the endogeneity concern by controlling for physician fixed effects and find evidence that detailing is informative about the negative features of the drugs being promoted. Manchanda, Rossi and Chintagunta (2004) take a different approach. They assume that detailing is allocated based on some prior knowledge about the estimated parameter values and deal with the endogeneity in detailing by incorporating a model for the marginal distribution of detailing, which depends on conditional response parameters, into the conditional model of the sales response. They show that physicians in their data are not detailed optimally: high-volume physicians are detailed too much without regard to responsiveness to detailing, suggesting the suboptimal allocation of sales force effort. Narayanan, Desiraju and Chintagunta (2004) explore the revenue impact of marketing-mix variables using aggregated data and find that detailing and advertising affect demand synergistically. They handle the endogeneity in detailing by using the number of employees from the annual reports as instruments. In investigating the effect of salespeople on purchase decisions, Jain, Misra and Rudi (2020) employ a control function approach to address the endogeneity concern in salesperson efforts using instruments pertaining to the supply of salespeople. Specifically, they use the number of salespeople in store, salespeople's past experience and their interaction with recent customers as instruments. They find that the effectiveness of salespeople diminishes with the sales force size. Compared to these studies, the current paper contributes to the literature by employing an NCF approach and leveraging the information on the salespeople assignment rule to handle the endogeneity issue.

This paper also contributes to the sales force literature by revealing some details about the decision-making process of salespeople assignment. In practice, firms often use heuristic or rule-based approaches to determine the sales force size (Sinha and Zoltners 2001, Albers and Mantrala 2008). Since these approaches do not directly focus on profits and ignore the impact of salespeople on revenue, they are likely to produce decisions biases from a profit-maximizing viewpoint. Previous studies focus on designing theoretically efficient sales force management (Lodish et al. 1988, Mantrala, Sinha and Zoltners 1992, Skiera and Albers 1998, 2008, Albers 2012). Although the gap between practice and theory of sales force management has long been recognized, the evidence on how firms manage the sales force is scarce, probably due to the fact that the specific rules implemented by firms are confidential. In this paper, we document the detailed salespeople assignment rule that gives us a glimpse of the underlying decision process.

Finally, this paper relates to the large literature on the compensation systems in sales force management. Theories suggest that salespeople's effort levels are strongly driven by compensation systems (Basu et al. 1985, Rao 1990, Mantrala, Sinha and Zoltners 1994, Raju and Srinivasan 1996). Steenburgh (2008) examines whether lump-sum bonuses motivate salespeople to work harder or induce salespeople to play timing games, i.e., behaviors that increase incentive payments without providing incremental benefits to the firm. Misra and Nair (2011) develop a structural model of sales-force compensation which explicitly incorporates the dynamics induced by agent behavior. They apply the model to evaluate changes in compensation plan, and these recommendations are then implemented at the focal firm. They find that the new plan results in a 9 percent improvement in overall revenues. Chan, Li and Pierce (2014) examine the impact of compensation systems on peer effects and competition in collocated sales teams. In our case, the compensation plan depends on the sales force size. Although the unobservability of effort levels prevents us from making a direct causal inference, our results indicate that assigning an additional salesperson lowers salesperson commission as well as attendance rate, which hints at a decline in effort levels.

3 Data description

3.1 Revenue

We obtain proprietary data from a leading cold drinks manufacturer in China.[4] The manufacturer produces fruit juice, yogurt, ready-to-drink coffee, etc. These products must be transported by cold-chain trucks and stored in freezers. The shelf life of these products is short, mostly between one and two weeks. To speed up the production-sale cycle, the manufacturer relies on frequent promotions and salespeople in stores.

The raw data consists of detailed information on all orders from all supermarket stores of six chains (major retailers of the manufacturer) in five major cities[5] in Southeastern China for 19 months, between January 2018 and July 2019. Based on our conversation with employees from the manufacturer, it is the sales representatives from the regional sales departments of the manufacturer, rather than the stores, who place these orders. We drop stores which shut down during the sample period out of the concern that those stores may shed inventory in clearance sales before closing. This leaves us with 231 stores.

To obtain the monthly wholesale revenues, we aggregate the order data over each

[4]We cannot reveal the name of the manufacturer for confidentiality reasons.

[5]The five cities are Shanghai, Nanjing, Jiangsu, Wuxi and Hangzhou.

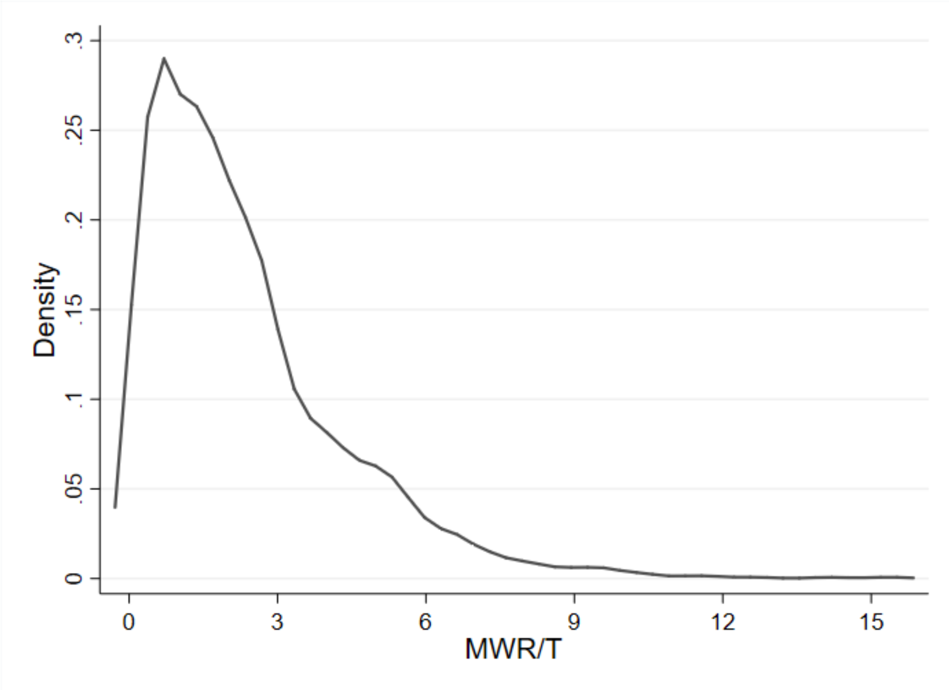

Figure 1: *The distribution of the monthly wholesale revenue relative to the threshold*

Note: This figure depicts the distribution (kernel density) of the monthly wholesale revenue (MWR) relative to T, where T is a threshold above which one salesperson will be assigned to the store.

month for each store. It is important to note that by revenues, we refer to wholesale revenues that the manufacturer receives from stores. The average MWR is $2.36T$ CNY, with standard deviation $2.01T$, where T is the threshold above which one salesperson will be assigned to the store. Figure 1 presents the distribution (kernel density) of MWR relative to T. We can see that most observations in the sample are located in the region where the ratios are less than 6.

3.2 Salespeople

Now we turn to salespeople. The salespeople, in fact, are not employed by the manufacturer directly. Rather, they are employees of third-party companies. Once employed by the manufacturer through third-party companies, salespeople's personal information would be recorded thereafter. Hence, we can track each salesperson even if she switches stores during the period. In the course of work, they wear store uniforms and recommend the manufacturer's products to customers passing by. Their job also includes monitoring and sorting inventories and freezers, dealing with products that are near the sell-by dates as tie-ins, and reporting sales to the sales representatives from the regional sales departments.

We collect the payroll records of all salespeople employed by the manufacturer and drop those who do not work in the sample stores during the sample period, which leaves

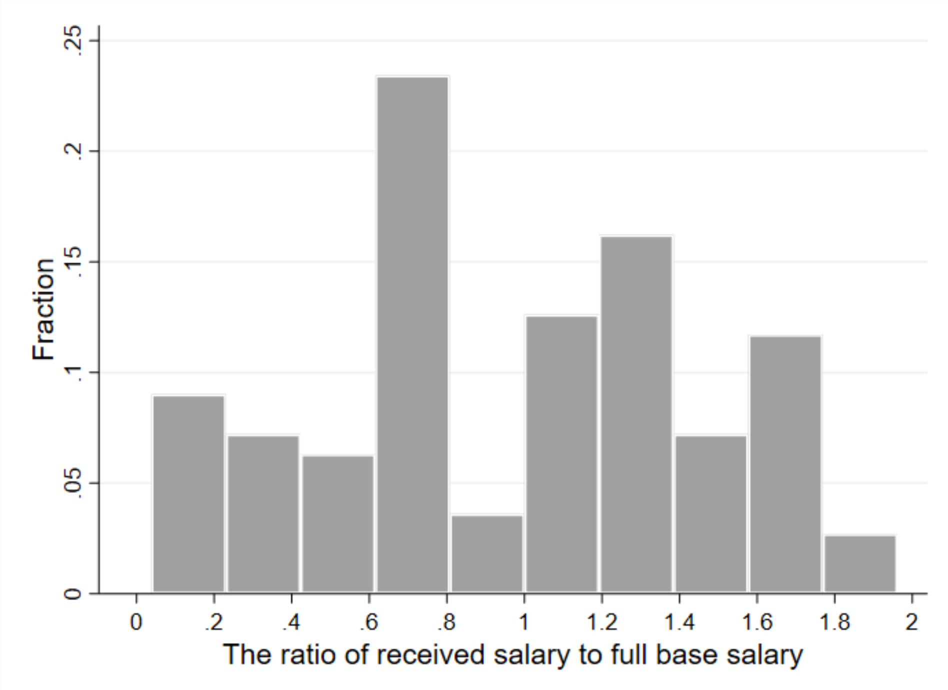

Figure 2: *The distribution of the ratios of the received salary to the full base salary (excluding salespeople who receive full base salary)*

us with 369 salespeople. Note that the number of salespeople in a store is between zero and two, varying across stores and over time.[6]

The manufacturer uses a quota-based compensation plan. Specifically, the manufacturer sets four quotas for each store, and a commission will be awarded based on the corresponding commission rate in addition to a fixed base salary. The higher the quota, the higher the commission rate. The salespeople in different stores have different base salaries, quotas and commission rates. In particular, the base salary is either 1600 or 2300 CNY, slightly above the local minimum wage. It is important to mention that when there is only one salesperson in the store, she will get 100 percent of the commission. When there are two, each salesperson will get 75 percent of the commission; that is, the total commission increases by only 50 percent instead of 100 percent. Also, the manufacturer subsidizes salespeople's telecommunication and transportation costs for about 200 CNY each month. On weekends and national holidays, overtime pay will be rewarded, which can be double or triple the average daily wage. Adding up all the income, the average salary is about 4000 CNY each month.

We do not directly observe the exact days that salespeople work in a month, nor do we directly observe the number of days. Nevertheless, the salary data provides a good measure of the number of days a salesperson works. A salesperson who is on duty on all working days within a month will receive a full base salary. A salesperson who is absent

[6]About 1.5 percent of store-month observations have three or more salespeople, possibly due to temporary reassignment.

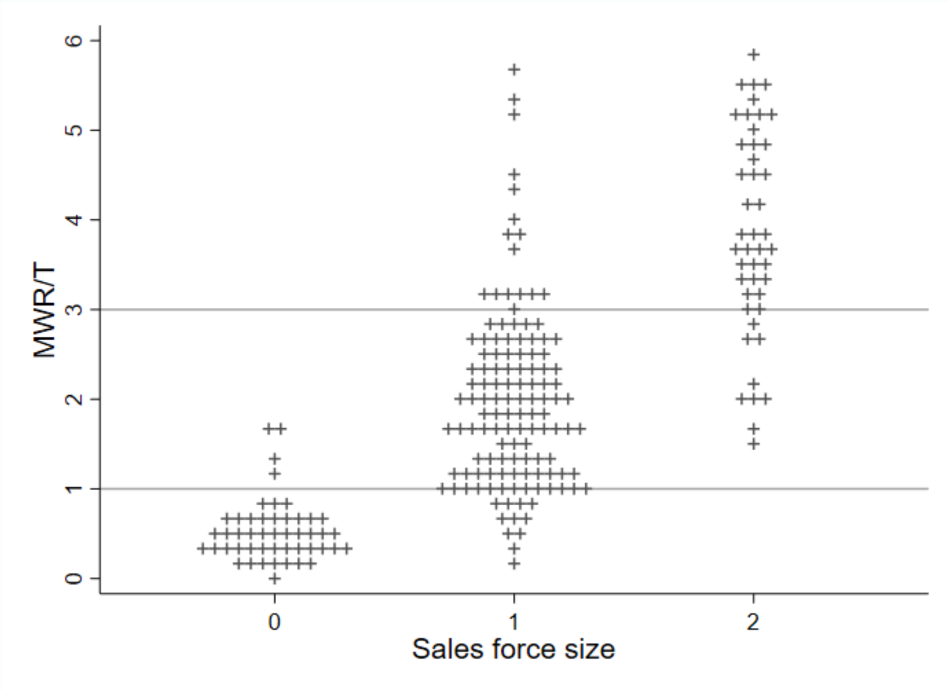

Figure 3: *The distribution of MWR by the number of salespeople*

Note: This figure depicts the distribution of monthly wholesale revenues (MWR) relative to T, where T is a threshold above which one salesperson will be assigned to the store, by the number of salespeople. The horizontal axis refers to the number of salespeople, and the vertical axis refers to MWR relative to T.

on certain days loses a fraction of the base salary depending on the number of days she is off. It is straightforward to define the number of salespeople for a store when they get the full base salary. For those who do not receive the full base salary, which constitutes only about 3 percent of the observations in our data, we present the distribution of the ratios of the received salary to the full base salary in Figure 2. We treat those who do not receive the full base salary as full-time salespeople if they get no less than 20 percent of the full base salary.[7] Based on this definition, about 54.0 percent of store-month observations are with one salesperson, and 24.3 percent are with two.

3.3 Assignment rule

The manufacturer decides on the number of salespeople in a store based on the previous MWR from the store. Due to fluctuations in MWR and the reassignment costs, a store may not adjust the number of salespeople every time the MWR exceeds or falls below the thresholds. But overall, the salespeople assignment rule based on the previous MWR is followed rather closely. Figure 3 shows a store's average MWR (normalized by T) against its number of salespeople. We can see that in most cases, the salespeople assignment to a store is "consistent" with the store's contemporary MWR.

[7] We also try 50 and 80 percent and find similar estimation results.

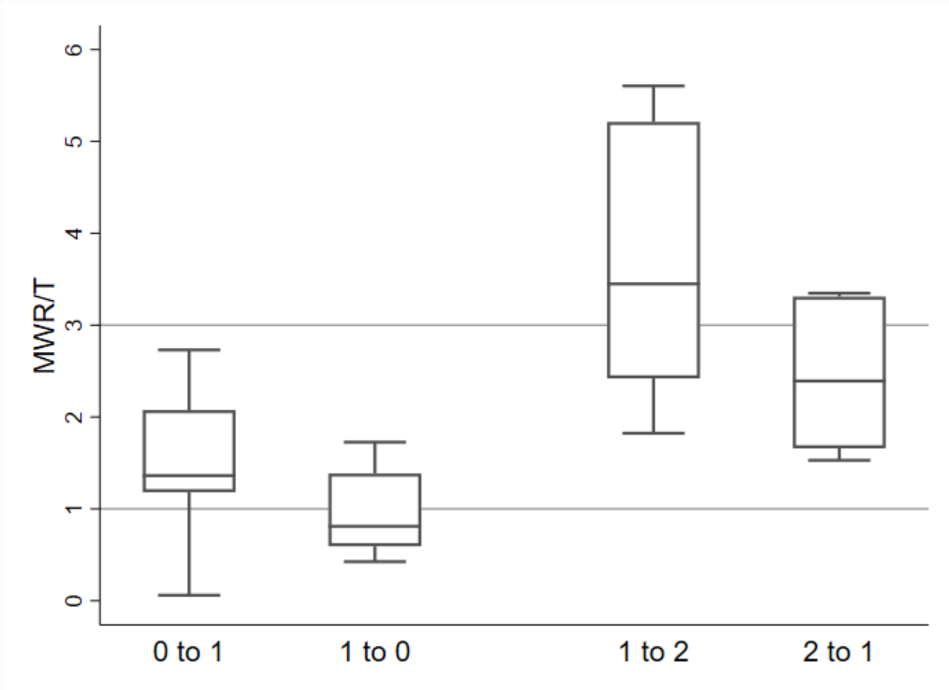

Figure 4: *The distribution of MWR relative to T before sales force size adjustments*

Note: This figure depicts the distribution of monthly wholesale revenues (MWR) relative to T, where T is a threshold above which one salesperson will be assigned to the store, before sales force size adjustments. The left two boxes refer to the cases where the number of salespeople goes from 0 to 1 and from 1 to 0, respectively. The right two boxes refer to the cases where the number of salespeople goes from 1 to 2 and from 2 to 1, respectively.

Next, we examine the cases in which the sales force size adjusts. Some changes in sales force sizes are not made by the manufacturer: this happens when a salesperson leaves for personal reasons, resulting in a temporary position vacancy. The manufacturer will assign a new salesperson to fill the vacancy in a relatively short period of time, generally within one month. Therefore, we drop these adjustments and identify 47 manufacturer-driven adjustments in the sales force size.[8] Of these 47 adjustments, there are 14 from 0 to 1, 10 from 1 to 0, 16 from 1 to 2, and 7 from 2 to 1.

We then put the "0 to 1" group and "1 to 0" group into one category, and the "1 to 2" group and "2 to 1" group into another. Instead of using current MWR relative to T as in Figure 3, we use the lagged term of MWR relative to T. Figure 4 is a box plot that depicts the distribution of MWR relative to T before sales force size adjustments. In the left category, we can find that the "0 to 1" group is not only larger than 1 for its median, but also basically higher than 1 as a whole, and the "1 to 0" group is less than 1 for its median. In the right category, it is clear that the "1 to 2" group is higher than 3 for its median and is basically higher than 3 as a whole, and the "2 to 1" group has

[8]We manually check whether the change in the sales force size is due to the manufacturer. In fact, if the change is due to the salesperson, the size will be back to the previous number in one or two months. If the change is due to the manufacturer, on the other hand, the change will last for a few months at least.

not only a significantly lower median, but also overall lower MWR relative to T than 3. Therefore, by comparing the MWR relative to T just before the manufacturer actively adjusts the number of salespeople, we find that the manufacturer does make salespeople assignment decisions based on previous MWR, and the assignment rule disclosed to us is followed rather closely.

4 Regression analysis

4.1 The effectiveness of salespeople

Our goal is to measure the causal effect of salespeople on revenue. The main empirical specification is

$$ln(MWR_{jt}) = \beta_1 D_{1,jt} + \beta_2 D_{2,jt} + \mathbf{X}_{jt}\gamma + \mu_{jt}, \tag{1}$$

where $D_{1,ij}$ equals one if there is at least one salesperson in store j in month t and zero otherwise, $D_{2,ij}$ indicates whether there are two salespeople, $\mathbf{X}_{jt}$ is a set of control variables, and μ_{jt} is an error term. The control variables $\mathbf{X}_{jt}$ include city, year-month dummies and lagged terms of $ln(MWR_{jt})$. By incorporating the lagged terms of $ln(MWR_{jt})$, carryover effect, defined as the effect of prior salespeople on current revenue, is also controlled (Manchanda, Rossi and Chintagunta 2004, Mizik and Jacobson 2004, Narayanan, Desiraju and Chintagunta 2004, Albers, Mantrala and Sridhar 2010). The coefficients β_1 and β_2 are of primary interest; they measure the effect of assigning one or two salespeople on revenue, respectively.

The endogeneity concern arises because revenue and number of salespeople are jointly affected by firms' optimal decisions. To address the endogeneity problem, we exploit the fact that sales force size adjustments are costly to firms, and thus predetermined rules are often adopted (as a way to approximate the optimal decisions, see Sinha and Zoltners (2001) and Albers and Mantrala (2008)). In our case, the manufacturer's salespeople assignment rules are defined by two MWR thresholds (i.e., T and $3T$). Specifically, the manufacturer assigns no salesperson to stores with previous MWR that is lower than T, assigns one salesperson to stores with previous MWR that is higher than T but lower than $3T$, and assigns two salespeople to stores with previous MWR that is higher than $3T$.

Based on the assignment rule, we construct an NCF to model the determination of $D_{1,ij}$ and $D_{2,ij}$.[9] Specifically, we estimate the following Probit models independently in

[9] A closely related approach is fuzzy regression discontinuity design, which can be viewed as a form of linear instrumental variable regression (Lee and Lemieux 2010). Here we use a non-linear instrumental variable (implied by the Probit model) to obtain more efficient estimates.

the first stage:

$$Prob(D_{1,jt}) = Prob(\sum_{\tau=1}^{N} \lambda_{\tau}^{1} I(MWR_{j,t-\tau} > T) + \mathbf{X}_{jt}\eta^{1} + \epsilon_{jt}^{1} > 0), \tag{2}$$

and

$$Prob(D_{2,jt}) = Prob(\sum_{\tau=1}^{N} \lambda_{\tau}^{2} I(MWR_{j,t-\tau} > 3T) + \mathbf{X}_{jt}\eta^{2} + \epsilon_{jt}^{2} > 0), \tag{3}$$

where $I(\cdot)$ indicates whether the condition in parentheses is met. The index N is the lag length, which we set at 3 for the main analysis, and then check robustness by either decreasing or increasing the lag length. The error terms ϵ_{it}^{1} and ϵ_{it}^{2} are assumed to be independently and normally distributed.

After estimating the two Probit models of the sales force size, we obtain the nonlinear fitted values $\hat{D}_{1,jt}$ and $\hat{D}_{2,jt}$. Then, following Angrist and Pischke (2008), we estimate the main Equation (1) via 2SLS using the fitted values as instruments for the endogeneous variables $D_{1,ij}$ and $D_{2,ij}$.[10]

Table 1 reports the estimation results of the Probit models. The two columns correspond to Equations (2) and (3), respectively. Because there is likely to be a serial correlation in the sales force size, we follow the standard practice to cluster standard errors at the store level (Bertrand, Duflo and Mullainathan 2004). From the first column, we can see that $I_{j,t-1}$, $I_{j,t-2}$, $I_{j,t-3}$ and $ln(MWR_{j,t-1})$ have significant coefficients but $ln(MWR_{j,t-2})$ and $ln(MWR_{j,t-3})$ do not, indicating that the decision of appointing the first salesperson follows the assignment rule quite closely. In column (2), coefficients of $I_{j,t-1}$, $I_{j,t-2}$ and $I_{j,t-3}$ are all significant, suggesting that the decision of appointing the second salesperson also follows the assignment rule. However, we can see that the coefficient of $ln(MWR_{j,t-3})$ is significantly positive and large in magnitude, indicating that the manufacturer is more cautious in appointing the second salesperson in the sense that the decision is based on the relatively long-term performance.

The estimation results of our main Equation (1) are reported in Table 2. Across all specifications, we include city and year-month dummies to control for common shocks to stores and cluster standard errors at the store level to address serial correlation in revenue. In column (1), we include no further controls. In column (2), we replace city fixed effects with store fixed effects. In column (3), we control for three lagged terms of $ln(MWR_{jt})$. Column (4) shows our preferred specification that implements the NCF approach discussed above. The results show that assigning one salesperson increases revenue by about 16.2 percent, while assigning an additional one further increases revenue by about 10.6 percent. This finding of the decreasing marginal effect of salespeople is

[10] Note that the endogenous variables in our case are dummies. To approximate to the conditional expectation function, we adopt a nonlinear specification. Nevertheless, using the nonlinear fitted values to estimate Equation (1) directly in the second stage is biased (Angrist and Pischke 2008).

Table 1: *The results for the Probit models of the sales force size*

	One salesperson	Two salespeople
	(1)	(2)
$I_{j,t-1}$	0.5772***	0.2653*
	(0.1286)	(0.1190)
$I_{j,t-2}$	0.2829*	0.3332**
	(0.1343)	(0.1233)
$I_{j,t-3}$	0.3338*	0.2117
	(0.1297)	(0.1159)
$ln(MWR_{j,t-1})$	0.3843*	0.5143*
	(0.1887)	(0.2197)
$ln(MWR_{j,t-2})$	0.3339	0.2516
	(0.2214)	(0.2429)
$ln(MWR_{j,t-3})$	0.2285	0.8766***
	(0.1953)	(0.2171)
City fixed effects	yes	yes
Year-month fixed effects	yes	yes
Pseudo R^2	0.5554	0.5303
No. of observations	3696	3696

Note: This table reports the results for the Probit models of the sales force size in Equations 2 and 3, with standard errors clustered at the store level in parentheses. The dependent variable equals one if at least one salesperson is assigned in the store and zero otherwise in column (1), and equals one if there are two salespeople in the store in column (2). The three independent variables (i.e., $I_{j,t-1}$, $I_{j,t-2}$ and $I_{j,t-3}$) refer to one to three months' lagged terms of indicators whether the MWR exceeds the thresholds T (column (1)) or $3T$ (column (2)).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

consistent with the literature (Manchanda, Rossi and Chintagunta 2004, Narayanan, Desiraju and Chintagunta 2004, Albers 2012, Jain, Misra and Rudi 2020). To assess the risk of a weak instruments problem, we find that the Cragg-Donald Wald F-statistic 324.048 is much larger than the critical values suggested by Stock and Yogo (2005), which suggests that the instrument constructed from the NCF is rather strong. Also, as a robustness check, we try two or four lagged terms of $ln(MWR_{jt})$ and find the results similar to the previous baseline analysis.

Note that controlling for the endogenous salespeople assignment (using the NCF approach) is important here: the results are substantially different from those obtained from other specifications. The result in column (1) shows that the effect of salespeople on revenue is largely overestimated when the endogeneity problem is not addressed at all. Also, comparing to our preferred specification in column (4), controlling for store fixed effects yields both economically and statistically insignificant coefficients for both $D_{1,jt}$ and $D_{2,jt}$ (column (2)), and adding lagged MWR yields much smaller coefficients (column (3)). A possible explanation for the results in columns (2) and (3) is that the manufacturer wishes to encourage promising stores with currently low revenue (conditional on the previous MWR), leading to a negative correlation between the sales force size and the error term. Therefore, only controlling for store fixed effects or lagged MWR results in underestimated effect of salespeople on revenue.

We conduct a simple benefit-cost analysis by computing the ratios of the revenue

Table 2: *The effects of salespeople on revenue*

	$ln(MWR_{jt})$			
	(1)	(2)	(3)	(4)
$D_{1,jt}$	0.9676***	0.0066	0.0531***	0.1617**
	(0.0254)	(0.0218)	(0.0123)	(0.0512)
$D_{2,jt}$	0.5430***	0.0056	0.0350**	0.1061*
	(0.0168)	(0.0206)	(0.0114)	(0.0436)
$ln(MWR_{j,t-1})$			0.5873***	0.5678***
			(0.0662)	(0.0672)
$ln(MWR_{j,t-2})$			0.1939**	0.1809**
			(0.0589)	(0.0556)
$ln(MWR_{j,t-3})$			0.1763***	0.1600***
			(0.0431)	(0.0387)
City fixed effects	yes		yes	yes
Store fixed effects		yes		
Year-month fixed effects	yes	yes	yes	yes
Adj. R^2	0.7340	0.9556	0.9552	0.9537
No. of observations	4389	4389	3696	3696

Note: This table reports the effects of salespeople on revenues using alternative approaches, with standard errors clustered at the store level in parentheses. The dependent variable is the monthly wholesale revenue (in logarithm). The independent variable $D_{1,jt}$ indicates whether there is at least one salesperson in store j in month t, while $D_{2,jt}$ indicates whether an additional salesperson is assigned in store j in month t. Across all specifications, we control for city and year-month dummies. In column (1), we add no further controls. In column (2), we replace city fixed effects with store fixed effects. In column (3), we control for three lagged terms of $ln(MWR_{jt})$. Column (4) shows our preferred specification that implements the NCF approach. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

generated by salespeople to their total salaries. To be specific, we calculate the revenue generated by salespeople based on the estimated effect of salespeople on monthly revenue, which is approximately a 16.2 percent increase in revenue when assigning one salesperson and 26.8 percent when assigning two salespeople (i.e., column (4) of Table 2). The total salary of a salesperson includes the base salary, the commission, the subsidy and the overtime pay.

Figure 5 depicts the distribution (kernel density) of the benefit-cost ratios across stores that have at least one salesperson. The ratio is 4.14 on average with standard deviation 1.91 and median 3.87. Therefore, on average, salespeople generate revenues approximately four times their costs. Note that we do not observe the sales profits, while evaluating the economic efficiency of salespeople requires comparing the cost of salespeople with the profit they generate. Supposing the profit margin is 25 percent,[11] the cost of salespeople is roughly equal to the profit they generated. When the profit margin exceeds 25 percent, the increase in profits generated by salespeople will exceed their costs.

[11] We define the profit margin as $(MWR - cost)/MWR$, where *cost* refers to all costs excluding the total salary paid to salespeople in store.

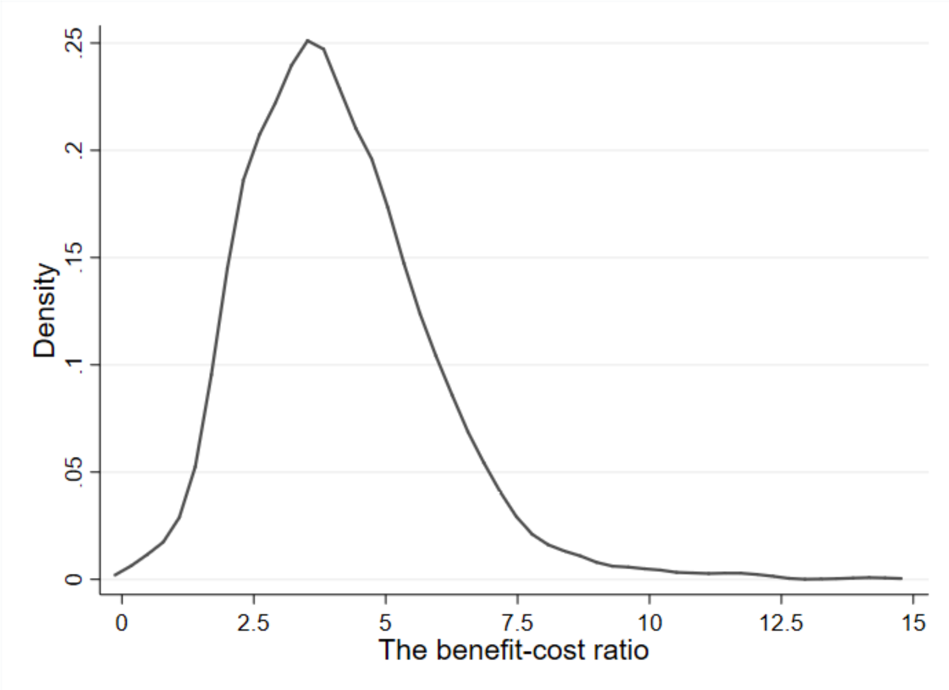

Figure 5: *The distribution (kernel density) of benefit-cost ratios of salespeople*

Note: This figure depicts the kernel density of ratios of the revenue generated by salespeople (i.e., benefit) to their total salaries (i.e., cost). The revenue generated by salespeople is based on the estimated effect of salespeople on monthly revenue, i.e., 16.2 percent increase in revenue when assigning one salesperson and 26.8 percent when assigning two salespeople. The total salary of a salesperson includes the base salary, the commission, the subsidy and the overtime pay. The sample includes stores that have at least one salesperson. Ratios larger than 15 are excluded.

4.2 The effect of compensation on incentives

In the preceding analysis, we find that the marginal effect of the sales force size on revenue decreases. In this section, we show that this empirical finding can be partially explained by the incentive issues caused by the manufacturer's compensation plan.

It is known that a worker's effort level is strongly driven by commission level (Ghosh and John 2000, Steenburgh 2008, Misra and Nair 2011, Chan, Li and Pierce 2014, Rubel and Prasad 2016). As discussed in Section 3, the commission a salesperson gets depends on the sales force size in the store. That is, when a second salesperson is assigned, each of the two salespeople gets only 75 percent of the commission. Given the reduced marginal return of working as a second salesperson, she may not have the incentives to make a full effort.

There is no doubt that neither researchers nor firms can observe salespeople's actual effort levels directly. Instead, we examine two indicators that may indirectly give us a hint of the effort levels. First, when an additional salesperson is assigned, does the commission level decrease? If so, it is reasonable that salespeople would not have the incentives to make a full effort. Second, when an additional salesperson is assigned, does the attendance rate decrease? That is, salespeople who tend to make less effort are likely

Table 3: *The decline in commission and attendance rate after assigning an additional salesperson*

	Commission		Attendance rate	
	(1)	(2)	(3)	(4)
$D_{2,it}$	-0.2652***	-0.1867**	-0.0146***	-0.0392*
	(0.0237)	(0.0626)	(0.0037)	(0.0163)
$ln(MWR_{it})$	0.9611***	1.5814***	0.0060*	0.0045
	(0.0271)	(0.0728)	(0.0028)	(0.0062)
Year-month dummies	✓	✓	✓	✓
Store fixed effects		✓		✓
Adj. R^2	0.722	0.665	0.011	0.020
No. of observations	3212	3212	3212	3212

Note: This table examines the difference in the commission and attendance rate of salespeople in stores with different sales force sizes, with standard errors clustered at the store level in parentheses. The sample includes store-month observations with at least one salesperson. The dependent variable is the commission of salespeople (in logarithm) in columns (1) and (2), and is the average attendance rate of salespeople in columns (3) and (4). The independent variable $D_{2,jt}$ indicates whether there are two salespeople in store j in month t. We control for year-month dummies across all columns and further control for store fixed effects in columns (2) and (4).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

to have a lower attendance rate.

To answer the questions, we examine the difference in commission and attendance rate of salespeople in stores with different numbers of salespeople. We focus on the subsample of store-month pairs with at least one salesperson and estimate the following model:

$$Outcome_{jt} = \beta D_{2,jt} + \mathbf{X}_{jt}\gamma + \mu_{jt}, \tag{4}$$

where $Outcome_{jt}$ is either the commission per salesperson[12] in store j in month t (in logarithm) or the average attendance rate of salespeople in store j in month t. To measure a salesperson's attendance rate in one month, we use the ratio of the received salary to the full fixed salary, which is a continuous variable between 0 and 1. The vector $\mathbf{X}_{jt}$ is a set of control variables, including the current MWR (in logarithm), year-month dummies. The coefficient β is of primary interest to us; it measures the average change in commission or attendance rate when the number of salespeople increases from 1 to 2.

Table 3 shows the estimation results. We include store fixed effects in columns (2) and (4) to control for any time-invariant unobserved heterogeneity across stores. Regarding commission, the coefficient of $D_{2,jt}$ is -0.27 in column (1) and -0.19 in column (2); both are statistically significant. Our preferred specification in column (2) suggests that salespeople who work with a colleague get 19 percent less commission on average than those who work independently. For the results of attendance rate, the coefficients are also both significantly negative with or without controlling for store fixed effects. The results in column (4) show that salespeople would work approximately one day less when

[12] The commission is identical for each salesperson in the same store with two salespeople.

an additional salesperson is assigned to the store.

Overall, the results suggest that the decreasing marginal return of an additional salesperson may be partially attributed to the design of the compensation plan. However, the results are not conclusive and should be interpreted with caution due to the lack of direct measures of effort levels.

5 Conclusions

Leveraging a unique retail sales data set from a leading Chinese cold drinks manufacturer and information on the implemented salespeople assignment rule, we measure the effect of salespeople on product revenue using an NCF approach to address the endogeneity issue in salespeople assignment. We find that assigning the first salesperson follows the assignment rule more closely than assigning the second one, suggesting that the decision on the latter is based more on long-term considerations. We also find that assigning one salesperson increases revenue by about 16.2 percent, while assigning an additional one further increases revenue by about 10.6 percent. In addition, we show that on average, salespeople generate revenues approximately four times their cost. Furthermore, our results highlight the importance of controlling for endogeneity in the number of salespeople and the usefulness of exploiting the firm's decision-making process when measuring the effectiveness of salespeople. Finally, to understand the decreasing marginal effect of the sales force size on revenue, we explore the effect of compensation on salespeople's effort levels by exploiting the change in compensation plan when an additional salesperson is assigned to the store. We find that a salesperson who works with a colleague gets 19 percent less commission and works one day less per month than one who works independently.

These findings have important managerial implications. Our results show that the salespeople assignment made by the manufacturer, which is based on the preset rule, is generally effective. While more flexible assignment rules may further enhance the effectiveness of salespeople, this may be accompanied by higher administrative costs. Therefore, the salespeople assignment rule we observe may be an approximation of the optimal assignment rule. In addition, our results show that the effect of salespeople on revenue decreases with the sales force size and that the commission of each salesperson is significantly lower after assigning an additional salesperson. Consequently, there is an interesting trade-off between reducing salespeople's payment and increasing revenue for firm managers. Improving the measurement accuracy of the ratio of the profit generated by salespeople to their costs can help firms make better decisions on salespeople assignment and compensation plan design.

Two limitations of the paper should be noted. First, we cannot directly observe the interactions between salespeople and customers from our data. Consequently, the mechanism by which salespeople influence customer decisions is unclear. Secondly, we do not observe salespeople's actual effort levels directly, which prevents us from conducting a causal inference of the effect of the compensation plan on salespeople's performance. New technologies, such as in-store cameras together with video analytics, might be useful in order to observe and quantify salespeople's effort levels. As a matter of fact, Jain, Misra and Rudi (2020) employ this technology to relate the informative role of salespeople to customers' purchase decisions in a context of cosmetics retail stores. Future studies may continue our work using direct-effort level data obtained from new technologies.

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