Believing in Analytics: Managers’ Adherence to Price Recommendations from a DSS

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Introduction

Fast-fashion retailer Zara sets a clearance sales period at the end of each season, during which a group of managers (one for each country) set weekly markdowns. They made these decisions based solely on inventory until 2008, when the firm implemented a decision support system (DSS) which suggests revenue-maximizing prices (Caro and Gallien 2012), but country managers were free to deviate from its recommendations. Although a pilot test showed that the DSS’s prices increased revenue, initial adherence was low, so Zara performed two interventions intended to increase it. In this paper, we use data collected by the company from 2011 to 2013 to answer two questions: (1) what was the effect of those interventions on managers’ adherence? (2) what drives the evolution of adherence during each season, as well as the magnitude and direction of their deviations?

A few works in the operations management literature study adherence to DSSs. Elmaghraby et al. (2015) do so in a B2B context, and Van Donselaar et al. (2010) do it for an ordering DSS; both are related to groceries, a market with stable demand, and relate adherence to costs. We, instead, study adherence in the context of fashion, with short life cycles and uncertain demand, and relate it to inventory and to two specific interventions. There is also a large body of literature on the psychology of DSSs and technology adoption (Cooper and Zmud 1990, Hoch and Schkade 1996, Venkatesh et al. 2003), but it is not specific to operational decisions. Our claim is that, by analyzing how humans interact with OM technologies, the academic community can learn how to design better DSSs to entice practitioners to use them. As stated in Bendoly et al. (2006), "when it comes to implementation, the success [...] relies heavily on our understanding of human behavior”.

Question 1: Effect of the Interventions on Adherence

Context. We study the effect of the two interventions that the company performed to entice managers to follow the DSS’s recommendations: (1) showing, in the DSS’s interface, the revenue metric $Y$ which was the algorithm’s objective function (a relative revenue measure between 0 and 1), starting in Summer 2011; (2) showing a reference point for that metric, which was their own $Y$ in the same week of the previous year, starting in Summer 2012. Note that, in some countries, Zara owns all of its stores. Managers of those countries are all located together in the company’s headquarters, and actively provided feedback on the DSS’s interface; therefore, the interventions
are endogenous to them. In the rest of countries in which Zara is present, its stores are franchises, and country managers are located separately. For them, the interventions were exogenous. Figure 1 shows the distribution of adherence for each season and type of country. We see that own-store country managers always showed higher adherence than franchises, and that the adherence of franchises increased drastically when the second intervention occurred, but not that of own stores.

![Figure 1: Distribution of managers’ adherence for each season and country type. The revenue metric intervention occurred in Summer 2011; the reference point intervention, in Summer 2012.](image)

**Methods.** To quantify the effect of those interventions, we compute the average adherence for each manager, season and product type to use as a dependent variable. We then run a linear fixed effects regression on indicators of each intervention plus all the available controls. We also run this regression separately for countries with Zara-owned stores and for franchises. To strengthen the case of a causal effect, we also run a difference-in-differences analysis. We split managers in three different pseudo-control/treated partitions. First, using own-store country managers (who showed high adherence before any intervention) as pseudo-control group, as the interventions were endogenous to them, and franchise managers as pseudo-treated. Second, using managers who already showed high adherence (top 25%) before each intervention as pseudo-control group. Third, analogous to the previous one, using the top 10% of highly adherent managers as pseudo-control.

**Results.** In both approaches, the linear FE and the DiD, the first intervention does not show a significant effect. The second one does, and it is all driven by franchises. For those countries, the coefficient estimate of the second intervention is close to 0.09 and significant at the 0.001 level.

**Discussion.** We see that showing them the value of the revenue metric they were maximizing did not affect their adherence, but showing it with a reference point increased it by 9 percent points.
for managers in franchise countries. This is consistent with the well-studied fact that humans are much better at interpreting quantitative information when it is framed in an appropriate context.

**Question 2: Evolution of Adherence During the Sales Season**

**Context.** Managers show inconsistent adherence within a season and, when they deviate, they usually set prices that are lower than the recommended ones. What drives the decision to deviate, as well as the magnitude of such deviations? We conjecture that they are minimizing inventory, as opposed to maximizing revenue, like they used to do before the implementation of the DSS.

**Methods.** We compute, for each product and week, the two main inventory variables that they considered before having the DSS, and which were also shown in its interface: (1) the speed of sales, as difference in sellthrough from one week to the previous one; (2) the remaining weeks to sellout at the current speed of sales. We also compute a variable of agreement between the DSS and a manager’s ”intuition”, which takes value 1 if a product is selling quickly and the DSS recommends no price cuts, or if it is selling slowly and the DSS recommends a price cut. We then run a Heckman regression, which analyzes the decision to deviate and the magnitude of such deviations separately. The dependent variable is the price markdown. We include all available controls in our regression.

**Results.** In both country types, if the DSS agreed with managers’ intuition, they were significantly less likely to deviate from it. Moreover, in the case of countries with Zara-owned stores, managers set higher prices when products were selling quickly, but this did not occur for franchise countries. When the salvage value of products was high, managers deviated less and set higher prices.

**Discussion.** Our results suggest that country managers were inventory minimizers, not revenue maximizers, especially when products had low salvage value at the end of the season. This can be explained by a number of well-known behavioral biases: loss aversion, time discounting, status quo bias, and salience/visibility of inventory. As future work, we will use structural estimation to replicate managers’ decision process, in order to disentangle their loss aversion from other biases.

**References**


