# Marketing’s Profit Impact: Quantifying Online and Offline Funnel Progression

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# 1. Background about Inofec BV and Managerial Problem

The specific focus of our study is on Inofec BV, a family-run European office furniture supplier operating in the Netherlands and Belgium. The company was founded in 1986 by the current CEO's father, and has grown into a medium sized firm of about 80 employees. The company shows average annual growth of about 20%. Their customers are professional end users and can choose out of an array of over 7000 SKUs. Inofec's main goal is to offer goods of high value at low costs. Their mantra: treat everyone as you want to be treated yourself. Their competitive advantage is adding a high level of service to their products (e.g., advice, assembling, and customized solutions) and having their own distribution network. Opposed to many bricks-and-mortar chains (e.g., Walmart, J.C. Penney) that allow customers to order online and pick up their purchase in an offline store, Inofec has no retail stores. Their service is to deliver the products to their customers, assemble the furniture, and only leave if the furniture is ready to use and the customer 100% satisfied. Furthermore, they spend a considerable marketing budget even during the current recession. The reaction of competitors to the recession has focused on slashing costs drastically – including layoffs and reorganization. In the words of Leon: *"Our competitors have an internal focus: angst management regarding preservation of jobs is key."*

Within this challenging environment, Leon, having a masters in marketing, realized that more insights could be gained from analyzing Inofec's own financial and marketing data. He sees the current situation not as a threat, but rather as an opportunity to invest in order to reap the benefits down the road. Leon is convinced that quantifying how customers move through the purchase funnel (i.e., information, evaluation, purchase) – and how marketing helps in this process – may lead to a sustainable competitive advantage. At the start of our cooperation, next period's sales figures and period-to-period comparisons represented the "state-of-the-art" techniques of allocation decisions and performance control at Inofec as well as their competitors. The effectiveness of marketing communication activities was monitored by observing subsequent sales changes – without considering long-term effects, cross-effects between channels, or controlling for other factors influencing sales. Allocation decisions were mainly based on gut feeling or "that's how we did it the last time". Against this background, Leon was looking for another perspective and was willing to adopt a marketing science approach.

The main marketing challenge facing Inofec was quantifying marketing communication activities' impact on purchase funnel stages (online and offline) and ultimately profits, and to reallocate the marketing communication budget accordingly. To this end, we jointly developed an approach to answer the following specific questions:

- Do Inofec's marketing communication activities only "feed the funnel" or do they also have an effect on later stages of the purchase funnel?
- What is the (net) profit effect of their marketing communication activities? Especially, what is the effect of "customer-initiated contacts" versus "firm-initiated contacts"?
- When does the effect of marketing communications "hit in" and how long does it last?
- How can Inofec improve its profits by reallocating its marketing budgets?

Answering these questions leads to an improved understanding of the role of marketing communication activities and planning of appropriate strategic actions. As such, it is of strategic importance since it may lead to a strategic change in the focus of activities. For example, if online activities are way more effective than offline activities as well as affect later stages in the purchase funnel, Inofec might need to focus more on their underrepresented online activities and explore new opportunities due to new technical developments.

## 2. Contribution to Literature – Extended Version

We contribute in four ways to existing literature: First, despite acknowledging the importance of multiple stages in the purchase funnel (e.g., Frambach et al. 2007, Gensler et al. 2009), many studies fall short in quantifying how they relate to each other (Ansari et al. 2008, Thomas and Sullivan 2005, Venkatesan et al. 2007, Naik and Peters 2009). This knowledge is important, as customers may prefer the efficiency of the online channel in the information stage, but then switch to offline channels to make the purchase. In such case, online activity should be 'credited' for the offline order. While customers may skip stages and switch channels between them, the role of each channel at different stages in the purchase funnel is of particular interest to companies (Naik and Peters 2009).

Second, many current studies do not consider dynamic effects because they are based on one-shot cross-sectional data (e.g., Ilfeld and Winer 2002, Powers and Menon 2008). Resulting recommendations regarding budget changes are uncertain to produce the desired profit change since differences between performance and marketing spending levels may be due to a host of other factors. Similarly, most studies do not account for feedback effects within a channel or across channels. For example, when website traffic increases, the firm may next experience a boost in offline information requests, after which the website is consulted again. Additionally, offline orders may lead to more offline and online leads because of word-of-mouth of satisfied customers (Ilfeld and Winer 2002, Keller and Fay 2009). Such performance feedback is an important and often overlooked aspect of marketing performance (Dekimpe and Hanssens 1999), as managers are interested in the total net profit impact of a marketing activity and its timing.

Third, previous research on allocating firm resources has focused on frequently purchased consumer goods (e.g. Biyalogorsky and Naik 2003; Deleersnyder et al. 2002). Likewise, almost all studies represented in meta-analyses of advertising effectiveness (e.g. Hanssens 2009, Hu et al. 2009, Lodish et al. 1995, Tellis 2004, 2009) concern business-to-consumer (or business-to-physician) settings. Lack of data is the main culprit: only one of the four industrial marketing effectiveness studies listed in Brand and Leeflang (1994), includes sales as a dependent variable – and it fails to find a significant marketing impact (Korgoankar et al. 1986). In a recent study of advertising effectiveness during recessions, Srinivasan and Lilien (2009) continue to report a paucity of previous studies on advertising effectiveness in business-to-business settings. Their own analysis shows similar effects of advertising on profits for business-to-business and business-to-consumer firms. However, advertising was measured as a percentage of sales from annual accounting data, while firms need to analyze their own, more frequently observed, data of different communication activities to derive actionable allocation insights. Thus, both academics and practitioners desire further knowledge on how to balance marketing investments in online and offline channels in a business-to-business context (ISBM 2008).

Finally, most academic studies did not have the cost data needed to calculate the return on investment of offline and online marketing spending and to make specific allocation recommendations. Especially for new marketing activities such as “customer-initiated contacts” (e.g., paid search advertising), the profit consequences have seldom been quantified, let alone compared to those of traditional “firm-initiated contacts”. Indeed, Shankar (2008) singles out “spending on unmeasured media such as search marketing” as an emerging research area.

# 3. Methodology

The VAR model in equation 1 is detailed below:

$$\begin{bmatrix} Catalog_t \\ Fax_t \\ Flyer_t \\ Adwords_t \\ eMail_t \\ Discount_t \\ OnVisit_t \\ OnLead_t \\ OnQuote_t \\ OnOrder_t \\ OffLead_t \\ OffQuote_t \\ OffOrder_t \\ Profit_t \end{bmatrix} = A_t + \sum_{k=1}^{K} B_k \times \begin{bmatrix} Catalog_{t-k} \\ Fax_{t-k} \\ Flyer_{t-k} \\ Adwords_{t-k} \\ eMail_{t-k} \\ Discount_{t-k} \\ OnVisit_{t-k} \\ OnLead_{t-k} \\ OnQuote_{t-k} \\ OnOrder_{t-k} \\ OffLead_{t-k} \\ OffQuote_{t-k} \\ OffOrder_{t-k} \\ Profit_{t-k} \end{bmatrix} + \Phi T_t + \sum_{i=1}^{6} \Gamma \times DOW_{it} + \Lambda \times HD_t + \begin{bmatrix} uCatalog_t \\ uFax_t \\ uFlyer_t \\ uAdwords_t \\ ueMail_t \\ uDiscount_t \\ uOnVisit_t \\ uOnLead_t \\ uOnQuote_t \\ uOnOrder_t \\ uOffLead_t \\ uOffQuote_t \\ uOffOrder_t \\ uProfit_t \end{bmatrix}$$

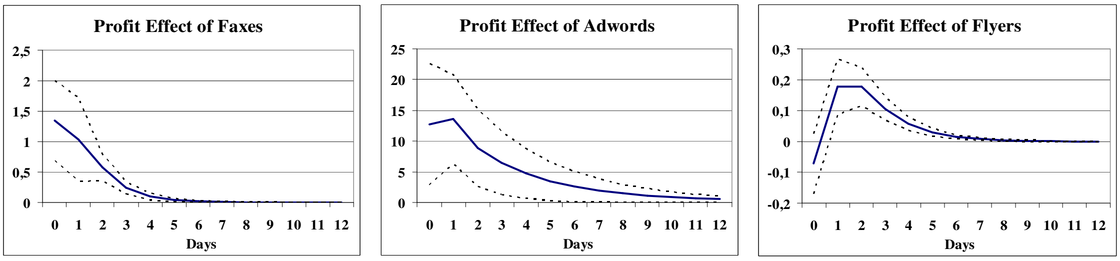
where $A_t$ is the 14x1 vector of intercepts, $T_t$ the 14x1 vector of time trends, $DOW_t$ the 14x1 vector with the 6 day-of-week dummies, using Friday as the hold-out, $HD_t$ the 14x1 vector of holiday dummies, and $[u_{Catalog\ t}, \ldots, u_{Profit\ t}]$ is the 14x1 vector of equation errors.

# 4. Additional Results

## 4.1 Effect Timing of Marketing Activity

The last three columns of Table 4 in the main paper display the number of days till the peak effect (wear-in) and the total number of days with significant profit effects (wear-out) and the total number of days covering 90% of the total effect. For instance, faxes achieved their impact on the same day (wear-in of 0), obtained significant profit effects for a total of six days (wear-out), and 90% of that effect occurred in the first four days. Moreover, Figure 1 below displays the unit profit responses (in Euros) to a one Euro increase in spending on respectively Faxes, Google Adwords, and Flyers, with standard error bands in dotted lines.

*Figure 1: Wear-In and Wear-Out of the Marketing Activities' Profit Effects*




For all marketing activities, the effects wear out rather soon: 90% of the total profit effect is achieved within seven days for Adwords, five days for emails and flyers, four days for faxes and one day for discounts. Our only comparison base for Google Adwords is Rutz and Bucklin (2008), who report that a generic search for lodging yields a peak in reservations after two days, and that 95% of the effect dissipates within 12 days. Similar to their industry setting, this suggests that Inofec's prospective customers tend to respond to marketing communication only when they are in the market for the company's products, and that most decide whether or not to purchase within a week. Such temporal dynamics bode well for Inofec's efforts to determine return on investment within a reasonable time frame, including the impact of substantially changing marketing activity spending in a field experiment.

As for the differences among marketing effect patterns, we observe that faxes achieve their largest impact immediately, followed by a fast and linear decline. In contrast, Adwords and Flyers effects take respectively one day and two days to "wear-in", after which wear-out (decay) is exponential. In response to Inofec's questions on these differences, we proposed that these temporal patterns are driven by the effect of different marketing activities on different stages of the purchase funnel.

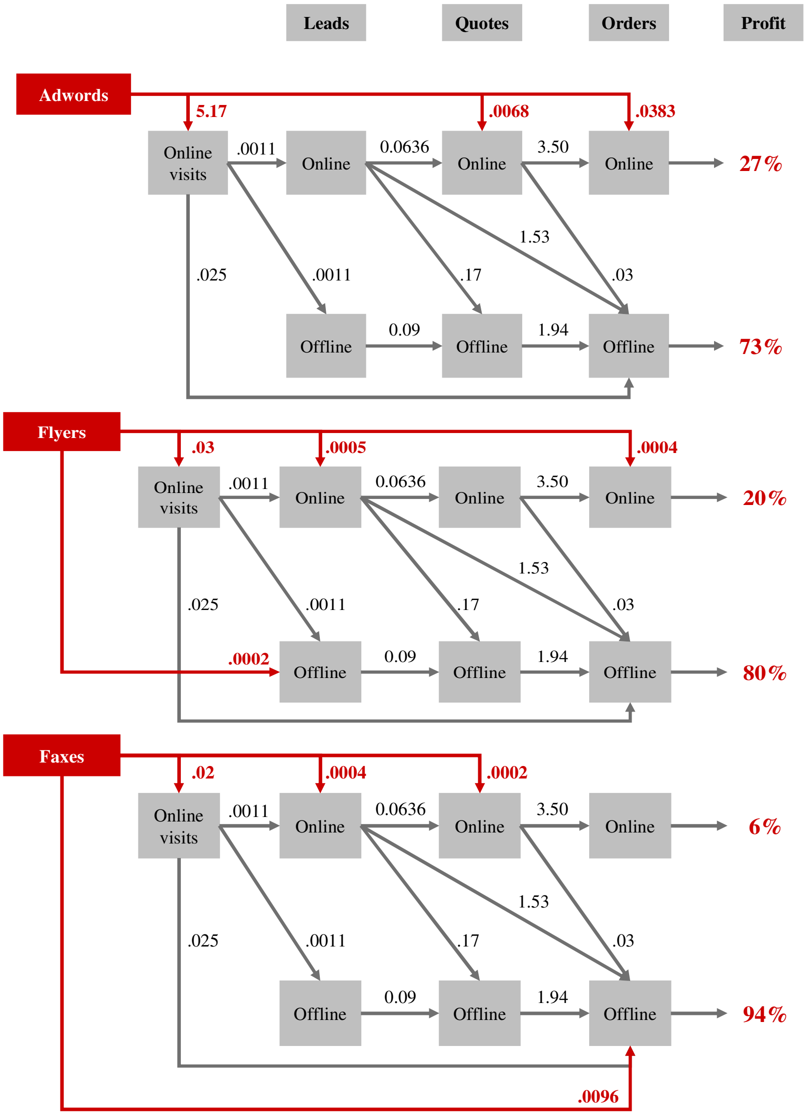
### 4.2 Effect on Purchase Funnel Stages

The VAR-model allows us to calculate the response of each endogenous variable to each other endogenous variable, and thus to quantify the effect for each stage of the funnel. Because catalogs were not found to have a significant impact, we focus on the remaining marketing communication activities.

Initially, we calculated only the effect of each stage on the next stage, with marketing communication activities only allowed 'feed the funnel'; i.e., having a direct impact on respectively website visits and offline information requests. While multiplying through these separate effects yields the total profit effect of emails, we found it underestimated the total profit impact of Adwords, Faxes and Flyers. Discussing these results with Inofec, we realized our omission of direct effects of marketing communication activities on later purchase funnel stages, which are part of our model. Based on the restricted impulse response analysis (Pauwels 2004), we found several additional effects of marketing, as displayed in Figure 2.

Faxes hardly 'feed the funnel' at all: they are unlikely to get the attention of prospective customers early on in the purchase funnel. However, they directly increase online information requests and quotes, and offline orders. The latter direct path represents 83% of faxes' total profit impact. Because of this direct effect on later funnel stages, the profit impact of faxes materializes and dissipates quickly. Higher spending on Google Adwords both feeds the funnel in the form of online visits, and increases online quote and orders, even keeping online visits constant. This illustrates the 'billboard' or 'inferred quality' effects of Google Adwords: we infer (in the absence of individual data, which Google does not share with anyone) that high paid search rankings increases the likelihood that a prospective customer, after having checked and dismissed competitive offering, progresses towards a purchase. Two thirds (66%) of Google Adwords impact is through the visits-offline orders path, explaining the longer wear-in of the profit effect of Adwords versus Faxes. Finally, flyers feed both the online and the offline funnels and yield profit through many paths, none of which dominates and all of which yield rather small profit effects in the end. As a result, flyers take longer to wear-in and have a smaller total impact on profits than either faxes or Adwords.

*Figure 2: How Marketing Activities Affect Purchase Funnel Metrics and Profits*




*Note: Bold arrows indicate significant effects from marketing activities on purchase funnel metrics; and the displayed numbers are the parameter estimates. Profit percentages are calculated as follows: (1) Multiplying the different paths marketing activities can lead to online or offline orders with the average value of an online/offline order, (2) summing up these resulting values, and (3) putting that in relation to the total profit impact of that marketing activity.*

Finally, Figure 2 shows a clear directionality of cross-channel effects. Offline marketing may affect online funnel metrics, but not vice versa. Conceivably, many prospective customers prefer to start the purchase decision process online, even when they noticed the firm's offline marketing activities. In contrast, online funnel metrics significantly affect offline funnel metrics, but not vice versa. In other words, some customers move from online to offline as their decision process moves from information, evaluation and finally action. This is consistent with prospects enjoying the search convenience of the Internet at early stages, and personal contact with salespeople at later stages of the purchase cycle.

Discussing our results, Inofec learned it is unwise to credit a marketing activity only for orders in 'its' channel, a practice typical for companies with different managers for different channels. This approach would be especially off for Google Adwords, which obtains 73% of its total profit impact from offline orders. In contrast, faxes and flyers obtain only respectively 6% and 20% of their profit impact from the 'other' channel.

### 4.3 Validation

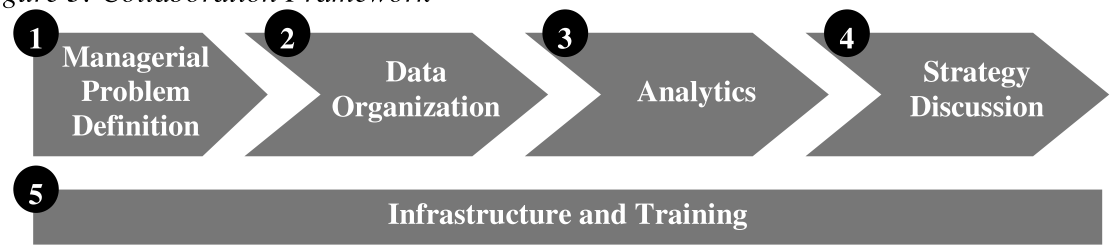
Besides verifying the absence of diminishing returns (see main paper), we also checked the robustness of our results by (1) changing the VAR lag specification, (2) including interaction effects and (3) estimating simple regressions to demonstrate that marketing activities may directly impact later purchase funnel stages, instead of having to go through the funnel 'hierarchy'. First, estimating the VAR-model of equation (1) with 2 and 3 lags yields virtually identical effect estimates as those obtained with the VAR(1) model, while the estimation efficiency declines. Moreover, adding specific lags of 7 days and 30 days (representing a week and a month) fails to improve the model. Thus, we find no reason to suspect that the lag order specification drives our results. Likewise, adding interaction effects of the marketing variables did not improve model fit. Next, for each of the identified 'direct' paths identified in the restricted policy simulation analysis, we estimated a series of regression models to validate that such direct effect exist. The Judd and Kenny (1991) procedure confirms in each case that mediation is only partial, leaving a direct effect. Therefore, we are not concerned that our evidence for these direct effects depends on the choice of procedure. Finally, we acknowledge the Lucas (1976) critique that any major policy change, e.g. one based on our recommendations, may change the data generating process and thus our key findings. To address this issue, we perform a field experiment over three months and analyze whether the experimental groups show changes in the profit effects of marketing activities (see main paper for results).

# 5. Organizational Impact

## 5.1 Collaboration Phases

Our collaboration with Inofec comprised several phases (Figure 3). First, beginning of 2007, we started by understanding Inofec's business and jointly defining the managerial problem. As said earlier, Inofec was looking for marketing science approaches that help them to quantify marketing communication activities' impact on the purchase funnel and ultimately profits. Second, we digged deep into Inofec's current databases and reorganized their data in a manner suitable for statistical analysis. This was quite a challenging task taking approximately 20 months, because Inofec logged data in different systems and changed database software several times over the last few years. Hence, information was not harmonized over time and not readily available for analysis. Third, we shared information on marketing science approaches to establish the right fit between the organizational problem and methodology. In doing so, it was important to first describe and discuss a descriptive model of the marketing-performance relationship. This made the mutual understanding way easier. Fourth, we discussed the results as well as the derived recommendations for Inofec's marketing strategy and deducted a field experiment to gain further insights. Finally, since 2007 we have trained and are still training a new employee who is responsible for marketing analytics and further we have improved managements' decision making process. The collaboration has not ended yet. Moreover, we are already in talks about next steps with respect to tackling newly emerged challenges due to the ongoing recession. Overall, Inofec appears satisfied with the collaboration. In a questionnaire about the collaboration, Leon answered the question with respect to how he feels about the joint project he says: *"It is extremely enjoyable, deeply inspiring. During the project, we picked up plenty of ideas, with which we started to experiment"*.

*Figure 3: Collaboration Framework*




1. Define managerial problem in collaboration with the company – duration: approx. 3 months
2. Leveraging data from existing systems (e.g., transaction, marketing databases) – duration: approx. 20 months
3. Employing marketing science approaches to derive insights from data – duration: approx. 3 months
4. Discussing results, designing strategies on data-driven insights, and deduct field experiment to gain further insights and validate results – duration: approx. 7 months and ongoing
5. Ongoing training in marketing analytics and improving the decision making process with existing information – duration: throughout the whole collaboration and ongoing

### 5.2 Impact Statement

Overall, our work has significant organizational impact along several dimensions:

*Cultural Impact.* Culturally, our work has changed the way Inofec allocates resources and employs marketing analytics in three important ways. First, prior to our work, the allocation of funds to different marketing activities was based on basic analyses, past experience, and "gut feeling". Not much effort had gone towards determining the profit effects of the activities and how management could leverage the existing data to gain insights regarding the effectiveness of the activities. Our approach brought about a fundamental change in the mindset and culture of the company with regard to marketing activities and their effectiveness. The current CEO and his father engaged in substantial discussions regarding the way of allocating resources as well as running the company. The culture has changed from allocating resources based on past experience and unorganized testing to one that considers a scientific way to gain insights and allocate resources for gaining competitive advantage and improving firm's profitability. Note that if a firm has been managed by intuition for many years, it is very unlikely to totally abandon "gut feeling". Given the complexity of marketing problems, a combination of marketing analytics and managerial intuition provides the best results for many marketing decisions (Lilien and Rangaswamy 2008). Accordingly, Inofec now uses both scientific approaches as well as intuition in order to make their decisions. Second, our results were not only discussed in the top management of the company, but throughout the firm, creating enthusiasm for executing the experiment to validate the recommendations. As such, our work is a basis for discussing the operational dimensions of Inofec's marketing activities, affecting the mental models of decision makers throughout the organization (Kayande et al. 2009). Such indirect benefits of model building are relevant and often overlooked (Leeflang et al. 2000). Inofec uses our results to evaluate the effectiveness of the post experiment communication activities and to decide on their resource allocation. We are currently working on a rolling windows approach to update the model estimates as new data comes in and the business environment changes. Moreover, we are developing a spreadsheet-driven dashboard tool that allows easy entry of potential marketing allocation plans and then uses the model estimates to project likely profit consequences (Pauwels et al. 2009). Finally, the ongoing training and increasing clout of the new employee, responsible for marketing analytics, is expected to help institutionalize the marketing scientific approach to allocating marketing resources – the final step in model adoption according to Davenport (2009).

*Methodological Impact.* Our approach has brought innovative and rigorous applications of marketing science to a small and medium size enterprise in the business-to-business sector. The most innovative aspects of our work relate to how we estimate the long-term and cross effects of marketing communication activities, analyze the funnel progression, and how we implement it. First, our approach uses an advanced econometric model to estimate direct, indirect and feedback effects of marketing communication activities on profit. Second, we realized that marketing activities not only "feed the funnel", but also directly impact later stages of the purchase funnel, controlling for the pass-through of earlier funnel stages. Third, we discussed the results of our analysis with Inofec and conducted a field experiment in order to further verify our results and improve confidence for major changes in Inofec's marketing budget allocation. Besides the contribution of the technical approach for practice and science, our work has helped Inofec to improve their internal process of how to deal with existing information as well as determining which other information should be collected. As outlined earlier, dataset integration enables Inofec for the first time to analyze the long-term profit impact of their different activities. Before the start of the project, this was not possible since (a) transactional data has been stored in different systems with different variables names and (b) transactional data was poorly linked to costs and timing of marketing activities as well as funnel metrics. Now, Inofec tracks details about their activities and links those to other data it has. Better dealing with existing information and knowing which new information should be collected are further important indirect benefits of model building (Leeflang et al. 2000).

*Strategic Impact.* Our work enables Inofec to determine the activities in which the company was generating or losing money and plan appropriate strategic activities. One of the main findings is the high effectiveness of online marketing activities such as paid search advertising and eMail campaigns. Paid search advertising was seen as something new, in contrast to the company spending the lion's share of its marketing budget – mostly unquestioned – on flyers. This 'bread-and-butter' marketing activity does not fare well in our analysis, yielding less than a Euro profit for every Euro spent. This improved understanding of the role of marketing communication activities has led to a strategic change in their focus of activities, as noted by Leon: *"The power and effectiveness of our website and Adwords were surprising. Based on that, we have an increasing interest in investing in online activities.*" Besides increasing the Adwords budget, Inofec is working in collaboration with their Google key account manager to optimize their paid search advertising. Another important finding was the cross-channel effects and the effect of marketing activities on later stages of the purchase funnel. Our decomposition helps the company better understand how profit changes are driven by changes in its marketing mix. This has led Inofec to rethink its strategies. As Leon says: *"We are going to design way more elaborate marketing strategies. In doing so, we will focus on the linkages between online and offline activities, explicitly distinguish the effects, and explore new opportunities due to new technical developments."*

*Financial Impact.* The results of the field experiment demonstrate the positive profit consequences of our recommendations. Compared to the base/base condition control group, doubling the Adwords budget yields a 7.51 times higher net profit increase. Similarly, halving the Flyers budget, but keeping the Adwords budget as is (low/base condition) results in 12.50 times higher net profit increase. Finally, following both our recommendation (decreasing the flyers and increasing Adwords – low/high condition) yields a 14.18 times higher net profit increase.

## 6. Transferability

While the specific focus of this paper is on Inofec BV, the need for accountability and practical marketing science tools in order to allocate one's marketing communication budget across media and online and offline channels is not limited to our partner firm. As Greg Welch, head of the CMO practice at Spencer Stuart, puts it: *"You have to be able to orchestrate a move towards emerging media. How do you take a traditional media budget and figure out not just how much to allocate to [new] media, but also how to measure it and how to defend it in front of your peer group"* (O'Regan 2007, p. 14). As such, our journey with Inofec included several insights we believe are valuable across settings. First, companies across industries continue to struggle with measuring the profit impact of new marketing tools such as customer-initiated contacts. Inofec's earlier budget allocation of 87% to traditional versus 13% to emerging tools is typical for established companies, despite the fact that many prospective customers are online (as evidenced in Inofec's case by the fact that 70% of the information requests are made online). Second, our analysis of indirect and direct marketing effects on purchase funnel metrics provides a rationale for the wear-in and wear-out of marketing effects on performance – a key managerial issue which has received little research attention. Third, many companies maintain separate accountability for online and offline marketing budgets and results, despite the suspicion of substantial cross-channel effects. Recent research has identified consumer preference for online-to-offline (web-to-store) shopping, and our empirical findings confirm this practice in a durable, business-to-business context. Our demonstration of the magnitude and direction of these cross-channel effects may inspire other firms to perform their own analyses. Fourth, our methodology has been shown to apply across vastly different industries such as business-to-business and fast moving consumer goods, durables and business content sites. However, validating its results and recommendations in a field experiment is new, and may inspire further testing of when the Lucas critique (1976) presents a substantial empirical challenge to the model's recommendations. Fifth, similar to Inofec, many firms posses huge amounts of data. Often, this data is not properly used since it is not well integrated ('data graveyards'). Harmonizing existing data in a manner suitable for analysis and employing relatively easy approaches to derive insights may already be a good starting point for many firms. This way, decision makers may be convinced about the potential of analytics and, in turn, may be more likely to also adopt more sophisticated marketing science approaches that are more difficult to understand. Finally, while various marketing science approaches exist, many managers are hesitating to adopt them and prefer to rely on their intuition. In order to increase adoption and success of our approach, we underwent the process outlined in Figure 3. Importantly, we incorporated the CEO as well as the new employee in each of the steps. For example, we defined the managerial problem together and the new employee was instrumental in harmonizing the data. Furthermore, we had regular intermediate meetings where we updated Inofec about our progress and presented insights generated until then. During those meetings, we discussed the next steps, the help needed from their side, and the potential questions that are possible to answer with our next analyses. This incorporation helped us in convincing Inofec about the usefulness of our approach since we provided them with feedback about the upside potential of applying marketing science approaches as well as guided them step by step in implementing it. In sum, the present study's insights on substantial cross-channel effects and direct marketing impact on later funnel stages are likely to transfer to other situations where managers aim to quantify long-term marketing effectiveness across channels. Furthermore, the collaboration process may be helpful in other situations where managers need to be convinced of the potential of marketing science approaches in order to adopt them for their own decision making.

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