16. How time series econometrics helped Inofec quantify online and offline funnel progression and reallocate marketing budgets for higher profits

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> *Analytical marketing is not very common in small- and medium-size enterprises in the business-to-business sector. As such, if we had a model or decision support system to enable us to decide how to allocate resources across communication activities and channels, we will have a huge advantage compared to our competitors.*
>
> Leon Suijkerbuijk, CEO of Inofec

THE COMPANY AND ITS CHALLENGES

Inofec BV, a family-run European office furniture supplier with about 80 employees, offers an array of over 7000 SKUs to professional end users. Having just taken over the helm from the company founder (his father), CEO Leon Suijkerbuijk saw a key opportunity for more profitable growth from analyzing Inofec's own financial and marketing data. So far, long-term effects or cross-effects between channels had not been considered, and allocation decisions were mainly based on gut feeling or "that's how we did it last time." Against this background, Leon was looking for another perspective and was willing to adopt a marketing science approach to answer the following specific questions: (1) Do Inofec's marketing communication activities only "feed the funnel" or do they also have an effect on later stages of the purchase funnel? (2) What is the (net) profit effect of their marketing communication activities? Especially, what is the effect of "customer-initiated contacts" versus "firm-initiated contacts"? (3) When does the effect "hit in" and how long does it last? (4) How can Inofec improve its profits by reallocating budgets?

To answer these questions, we (Wiesel, Arts and Pauwels 2011) worked with the company in the several phases outlined in Figure 16.1. The first phase consisted of jointly defining the managerial problem and mapping out the online and offline funnel for this company. The second phase leveraged data from the distinct databases, which turned out to be the most

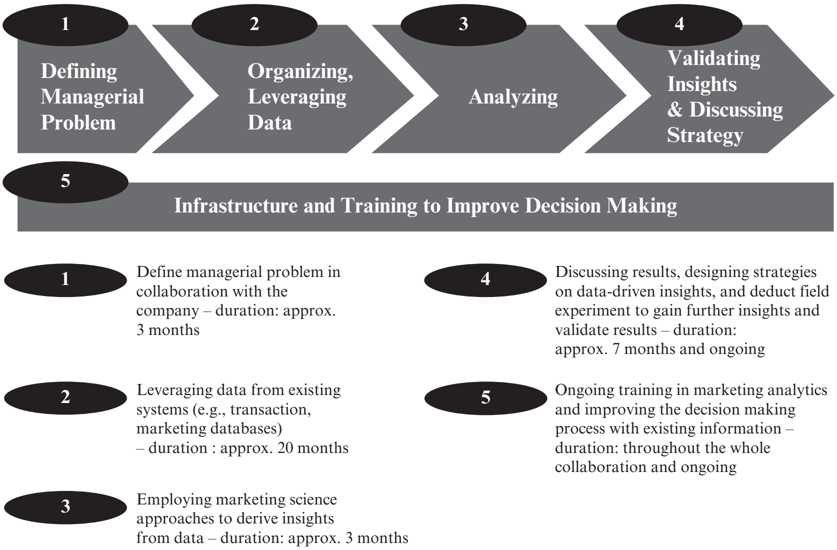


Figure 16.1 Collaboration process in key phases

time-consuming part of the project. In the third phase, we established the right fit among organizational problem, data and methodology, and estimated the time-series model. The fourth phase saw the design and use of an analytic dashboard based on the model estimates, which created the enthusiasm for running a field experiment. Finally, ongoing is the process of training employees in the use of analytics, and in further improving the model, dashboard and decision making.

MAPPING OUT INOFEC'S OFFLINE AND ONLINE PURCHASE FUNNELS

Our conceptual framework (Figure 16.2) focuses on the effect of marketing communication activity on profits, accounting for dynamic effects among purchase funnel stages in both offline and online channels, and feedback effects within and across channels.

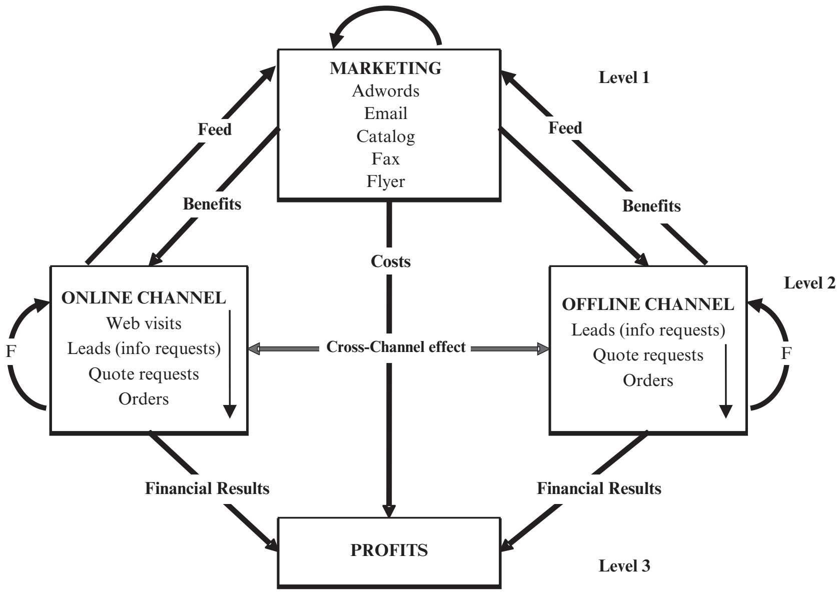


Figure 16.2 Conceptual framework

Marketing Activity: Firm-initiated Contacts and Customer-initiated Contacts

Depicted as level 1 in Figure 16.2, organizations use different marketing communication activities in order to generate revenue and move customers through the purchase funnel. Broadly speaking, we distinguish "firm-initiated contacts" (FICs) from "customer-initiated contacts" (CICs), which require the prospective customer to take an action (e.g., click on an ad) before the company is charged. Inofec has only recently started to spend on CICs in the form of search engine ads (about 13 percent of the total marketing budget), and management was doubtful about the incremental revenues generated. In contrast, it had always spent heavily (about 70 percent of the budget) on direct mail (flyers), followed by fax and email campaigns to prospective customers. Finally, the percent discount given to customers was believed to strongly drive demand.

Channels and Purchase Funnel Stages

Depicted as level 2 in Figure 16.2, customers' channel preferences can switch as they move closer to purchase. For the online funnel, web visits and leads (information requests) signal the beginning of the purchase process. Request for quotes (via the website) indicates that the prospective customer is evaluating the offer. Finally, orders (via the website) is a straightforward variable representing actual purchase. For the offline funnel, the variables are similar, except that we do not observe an equivalent measure to web visits.

Marketing Effects on Purchase Funnel Stages

Both online and offline marketing activity may ultimately generate profits (level 3 in Figure 16.2) by inducing prospective customers to start/finish their purchase process either online or offline. Customers may search online when the need arises for office furniture, visit the website to ask for information, but then call up the salesforce for the final quote and order (cross-funnel effects). Moreover, a marketing exposure or touch point may increase conversion down the funnel. For instance, being exposed to paid-search ads may increase the prospect's familiarity with the brand, while a well-designed catalog in the mail can signal the high quality of the company and its product. Both instances may increase customer conversion in later stages. In our framework and model, we account for both: marketing activities can affect the beginning but also later stages of the purchase funnel.

ORGANIZING AND LEVERAGING THE DATA

Before the time-series model could be estimated, we had to prepare the data coming from four databases: transactional (order volume, sales price and cost of goods sold), marketing spending, online purchase funnel and offline purchase funnel. The analysis was at the daily level since marketing actions varied daily and we aimed to identify funnel progression, which typically occurs over a few days. Operationalizing the variables as shown in Table 16.1, our data covered 876 days (over 2.5 years) across 12,000 customers. Leveraging the data for model-free insights, we observed the online channel was more popular for information requests (online leads are higher than offline leads), but the offline channel was more popular for quote requests and orders. In addition, the average offline order was slightly higher than the average online order.

Table 16.1 Variable operationalization

	Variable	Operationalization
Marketing activity	Catalog	Daily cost of catalogs (0 on days with no catalogs sent)
	Fax	Daily cost of faxes (0 on days with no faxes sent)
	Flyers	Daily cost of flyers (0 on days with no flyers sent)
	Adwords	Daily costs of pay-per-click referrals
	eMail	Daily number of net emails (sent minus bounced back)
	Discounts	Percentage of revenue given as a discount
Online funnel	Web visits	Daily total amount of visits to the website
	Online leads	Daily requests for information received via the website
	Online quotes	Daily requests for offers received via the website
	Online orders	Daily number of orders received via the website
Offline funnel	Offline leads	Daily requests for information received via sales reps, telephone or mail
	Offline quotes	Daily requests for offers received via sales reps, telephone or mail
	Offline orders	Daily number of orders received via sales reps, telephone or mail
Performance	Sales revenues	Daily sales revenues
	(Gross) profit	Daily revenues minus cost of goods sold

ANALYSIS AND RESULTS

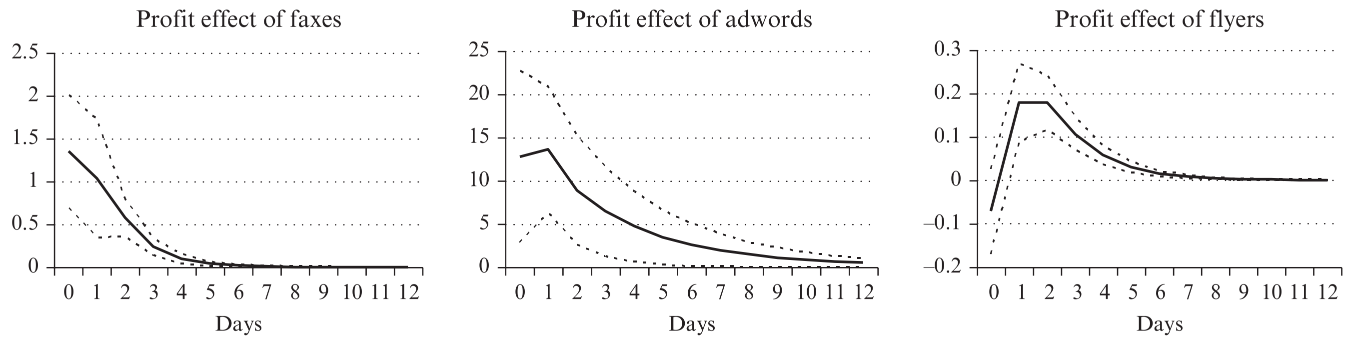
We extended the persistence modeling approach (Dekimpe and Hanssens 1999) to account for dynamic and cross-channel effects. Specifically, we estimated a vector-autoregressive (VAR) model with 14 regression equations; explaining both online (Google Adwords, email) and offline (fax, flyer, catalog and discounts) Marketing, Online purchase funnel metrics (web visits, online leads, quote requests and orders), Offline purchase funnel metrics (offline leads, quote requests and orders) and Profits (revenues – costs of goods sold). As control variables, we included an intercept C, a time trend T, day-of-week seasonal dummy variables (using Friday as the benchmark), and dummy variables for holidays. The model explained 77 percent of the variation in profits (adjusted $R^2 = 0.76$).

Figure 16.3 shows estimated impulse response functions, i.e., the profit effects for €1 spent on the three main marketing activities. Table 16.2 derives from these figures the total (cumulative) profit effect, including the number of days till the peak effect (wear-in period) and the total number of days with significant profit effects (wear-out period).

Catalogs showed no significant profit effects. While faxes achieved their peak impact on the day sent (wear-in of 0), Adwords took one day and Flyers took two days to do so (wear-in of 2). Interestingly, the effect of faxes also wore out quickly, while Adwords and Flyers continued to affect purchases for at least one week. In response to Inofec's questions about these differences, we proposed that these temporal patterns were driven by the effect of different marketing activities on different stages of the purchase funnel. Based on the restricted impulse response analysis (Pauwels 2004), we estimated the separate effects of each marketing activity on the online and offline funnel stages, as shown in Figure 16.4.

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 percent 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 quotes 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-level data, which Google does not share) that high paid-search rankings increase the likelihood that a prospective customer, after having checked and dismissed competitive offerings, progresses towards a purchase. Two-thirds (66 percent) 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 dominate 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.

Finally, Figure 16.4 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 to evaluation and finally to action. This is consistent with prospects enjoying



Note: * Profit effect estimate of 1 euro spent in solid line, standard error bands in dotted lines.

*Figure 16.3 Wear-in and wear-out of the marketing activities' profit effects**

Table 16.2 Marketing's total profit effect, sales elasticity and its timing in days

Variable	Profit effect	Sales elasticity	Wear-in	Wear-out
Fax (€)	3.33	0.05	0	6
Flyers (€)	0.57	0.04	2	9
Adwords (€)	55.72	4.35	1	9
eMail (each)	0.71	0.12	2	5
Discount (1%)	789	0.75	0	2

the search convenience of the Internet at early stages, and personal contact with salespeople at later stages of the purchase cycle.

DISCUSSING STRATEGY OPTIONS AND VALIDATING INSIGHTS IN A FIELD EXPERIMENT

Discussing our results, Inofec concluded 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 suboptimal for Google Adwords, which obtains 73 percent of its total profit impact from offline orders. In contrast, faxes and flyers obtain only 6 percent and 20 percent of their profit impact, respectively, from the "other" channel. Moreover, managers were surprised to learn that flyers, the activity that consumes 70 percent of the marketing budget, brings in less money than they spend on it. Upon reflection, they attributed this finding not to inherent issues with the marketing channel or its ad message (which is basically the same across channels), but to overspending: when anticipating a sales slump, Inofec had often started sending flyers to contacts on third-party lists of new businesses – many of which are not in the market for its products. In contrast, people searching for "office furniture" online (and then clicking on a paid search ad) have self-revealed to be in the market for such furniture.

The results and subsequent discussion allowed us to design the marketing dashboard in Figure 16.5, which enabled decision makers to perform "what-if" analyses that showed the projected profit implications of considered budget changes. Using the dashboard led managers to the risky strategy recommendations of (1) decreasing spending on flyers, (2) increasing spending on Adwords. As to the other actions, managers saw increasing emails as low cost and relatively risk-free, while they knew that increasing spending on faxes was not feasible due to a new Dutch law

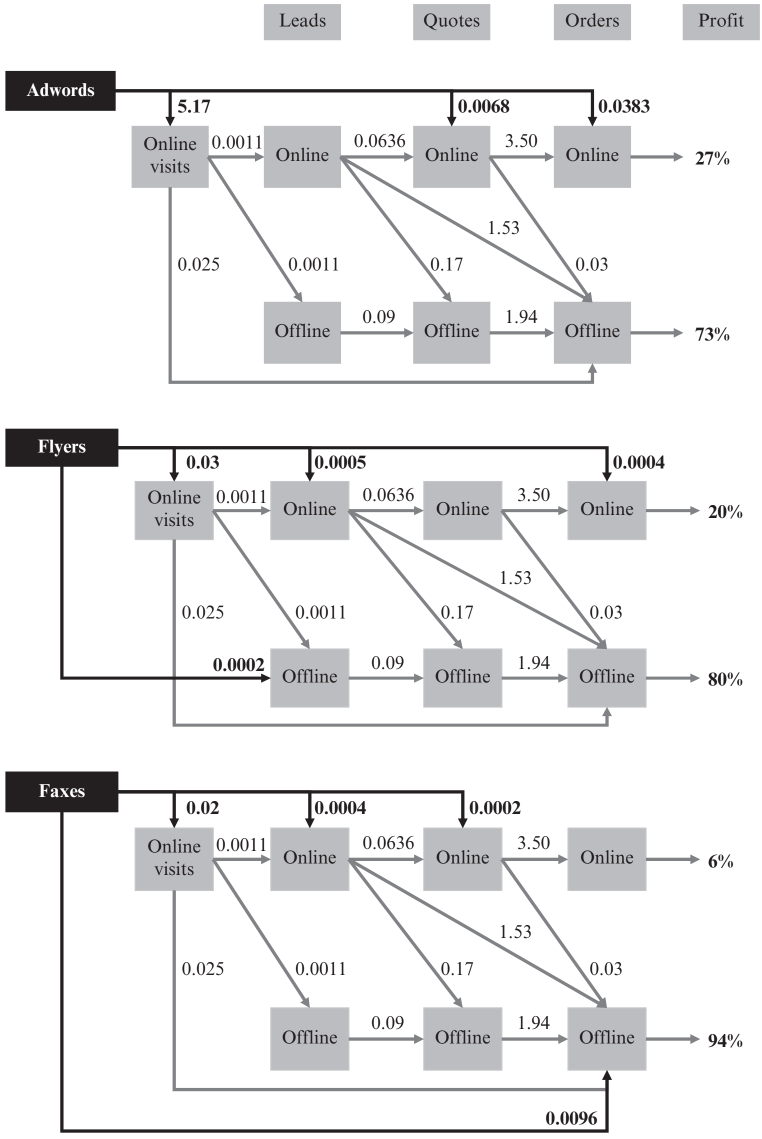


Figure 16.4 How marketing activities affect purchase funnel metrics and profits

Marketing Dashboard Prototype

Period	Flyers	Faxes	Adwords	Discount
1	0	400	100	7
2	0	0	50	7
3	0	0	50	7
4	4000	0	100	7
5	0	0	100	7
6	0	0	100	7
7	0	400	100	7
8	0	0	100	7
9	0	0	50	7
10	0	0	50	7
11	4000	0	100	7
12	0	0	100	7
13	0	0	100	7
14	0	0	100	7

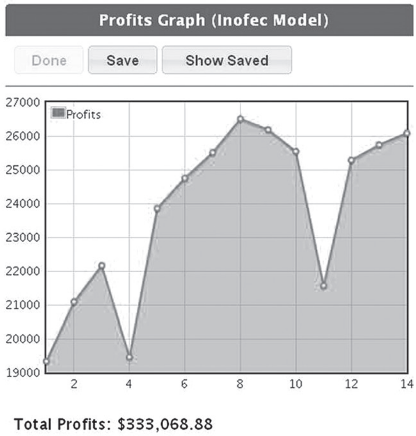


Figure 16.5 Marketing dashboard showing the projected profits of spending allocations

against unsolicited faxes. Instead of rolling out the strategy recommendations immediately, we instead validated our model in a field experiment. Specifically, we divided Inofec's market in four comparable regions and ran a 2 × 2 field experiment with a base (no changes in the planned flyer campaigns) and low-spend condition (halving flyers spending), and a base and high condition (doubling spending) for Adwords. This allowed us to separately test the impact of reducing spending on the ineffective marketing action (keeping others constant) – as managers contemplate in crunch times with cost savings demands, and the impact of increasing spending on the effective marketing action – as managers contemplate in boom times with revenue growth demands. After the experiment had run for three months, we compared daily net profits (net of marketing costs) with a difference-in-differences approach.[1] Table 16.3 shows the results.

While the control conditions saw daily net profits increase by €11 during the experiment (likely due to increased furniture demand), the experimental condition applying both recommendations saw profits increase by €154, i.e, a 14-fold higher profit increase than the status quo. Interestingly, only applying one part of the recommendation also substantially increased net profits. When the company's strategy focused on higher growth, Inofec could double Adwords without decreasing flyers (yielding €81 more net daily profits). In contrast, when the focus was on efficiency (e.g., because budgets were tight or needed for other actions), the company

Table 16.3 Daily net profit changes during the experiment versus before the experiment

		Adwords	
		High	Base
Flyers	Base	€ 81.39	€ 10.84
	Low	€ 153.71	€ 135.45

could simply cut the least efficient activity of flyers, while maintaining spending on Adwords. To validate that our estimated effect sizes would still hold up after such a substantial policy change, we re-estimated our model on the 91 days of data during the experiment, and indeed found similar coefficient estimates. The one exception was that each euro spent on flyers now returned 0.92 euros in the lowest marketing spend condition. This was consistent with Inofec's explanation that diminishing returns were to blame for the original findings and suggested that flyers should not be cut much more.

ONGOING LEARNING AND ORGANIZATIONAL IMPACT

This case study changed the organization as it led Inofec to rethink how it makes decisions. Since its inception, the company was managed by intuition. Hence, it was unlikely to totally abandon "gut feel" in decision making. Given the complexity of marketing problems, the literature suggests that 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. Moreover, our work became 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). We developed a spreadsheet-driven dashboard tool – including a rolling windows approach to update the model estimates – 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 a new employee, in charge of 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). As Inofec's CEO concluded: "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."

NOTE

1. For each condition, we subtract the gross profits in the three months preceding the experiment from gross profits in the three months of the experiment, and then scale each condition's profit change by the national average profit change (to control for seasonal and general economy factors that may boost or depress profits in all conditions).

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