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Practice Prize Paper

Marketing's Profit Impact: Quantifying Online and Off-line Funnel Progression

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Inofec, a small- to medium-sized enterprise in the business-to-business sector, desired a more analytic approach to allocate marketing resources across communication activities and channels. We developed a conceptual framework and econometric model to empirically investigate (1) the marketing communication effects on off-line and online purchase funnel metrics and (2) the magnitude and timing of the profit impact of firm-initiated and customer-initiated contacts. We find evidence of many cross-channel effects, in particular, off-line marketing effects on online funnel metrics and online funnel metrics on off-line purchases. Moreover, marketing communication activities directly affect both early and later purchase funnel stages (website visits, online and off-line information, and quote requests). Finally, we find that online customer-initiated contacts have substantially higher profit impact than off-line firm-initiated contacts. Shifting marketing budgets toward these activities in a field experiment yielded net profit increases 14 times larger than those for the status quo allocation.

Key words: profit impact of marketing activities; off-line and online; persistence modeling; field experiment
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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, personal communication)

1. Introduction

The above quote by the CEO of Inofec BV (our partner firm) illustrates a typical challenge facing firms: at a time of product commoditization, business processes are among the last remaining points of differentiation (e.g., Davenport 2006). Allocating firm resources across channels and communication activities becomes an important question (Neslin et al. 2006, Neslin and Shankar 2009). Analytical marketing can assist firms in making sound decisions about their marketing resource allocation. It is based on the idea that marketing decisions can be supported with analytical mathematical models as opposed to purely based on judgment and experience (Wierenga 2008).

The specific focus of this study is on Inofec BV, a family-run European office furniture supplier with about 80 employees. It offers an array of more than 7,000 stock-keeping units to professional end users. The current CEO, Leon, sees the economic situation not as a threat, but rather as an opportunity to gain more insights from analyzing Inofec's own financial and marketing data. Until this point, long-term effects or cross-effects between channels were not considered, and 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 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?

Answering these questions leads to an improved understanding of the role of marketing communication activities and planning of appropriate strategic actions as well as contributes in four ways to existing literature. First, we investigate the role of each channel at different stages in the purchase funnel, which is of particular interest to companies and academics (Naik and Peters 2009, Frambach et al. 2007, Gensler et al. 2010). Second, we consider dynamic effects as well as feedback effects within a channel and across channels. Not doing so might bias recommendations because differences between performance and marketing spending levels may be due to a host of other factors and/or overlook the total net profit impact of marketing activity. Third, we investigate the marketing effectiveness in a business-to-business setting. Most previous research on allocating firm resources has focused on frequently purchased consumer goods (e.g., Biyalogorsky and Naik 2003, Deleersnyder et al. 2002). Finally, we make specific allocation recommendations for new marketing activities such as customer-initiated contacts (e.g., paid search advertising) and compare them with those of traditional firm-initiated contacts.

The remainder of this paper is organized as follows. In the next section, we provide the research framework for answering Inofec's management problem. In §3, we describe the data; §4 contains our modeling approach, and §5 discusses our empirical findings. In §6, we describe our recommendation to Inofec to reallocate the marketing budget and the design and results of our field experiment. Next, we discuss the impact of our project. Finally, §8 comments on the transferability of our approach to other settings and concludes our paper. More details about our methodology, results, and collaboration process are provided in the electronic companion to this paper, available as part of the online version that can be found at http://mktsci.pubs.informs.org/.

2. Research Framework

Our conceptual framework (see Figure 1) focuses on the effect of marketing communication activity on firm profit in a durable and business-to-business context, accounting for dynamic effects among purchase funnel stages in both off-line and online channels, and feedback effects within and across channels. Subsequently, we focus on three key aspects of this framework: (1) marketing activities, (2) channels and purchase stages, and (3) how they are affected by marketing activities.

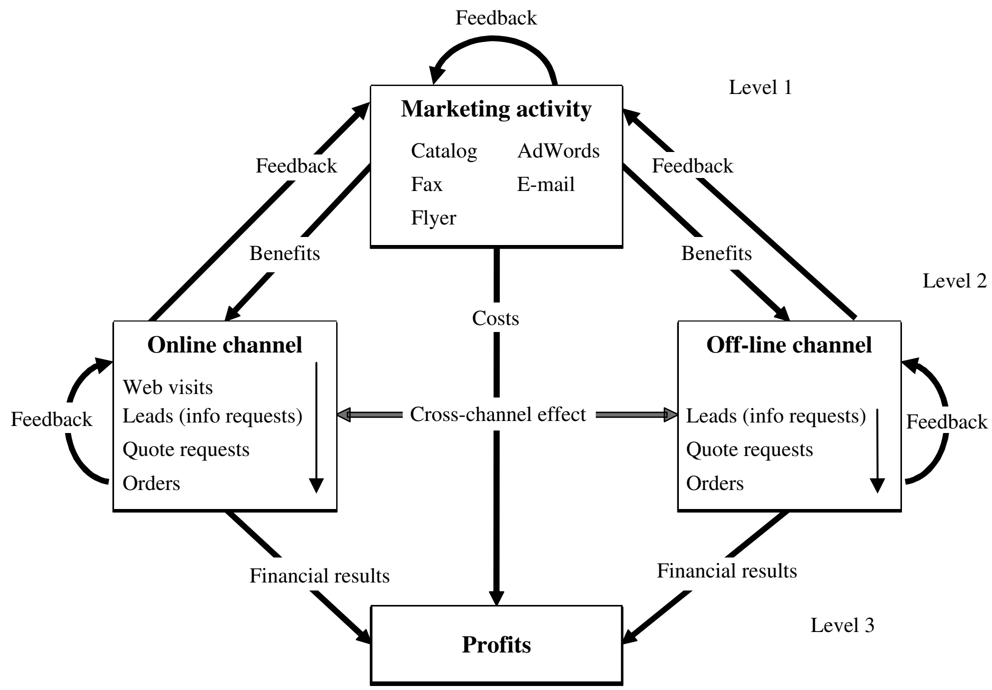
2.1. Marketing Activity: Firm-Initiated Contacts and Customer-Initiated Contacts

Depicted as level 1 in Figure 1, firms posit a toolbox of different direct marketing communication activities in order to generate revenue and move customers through the purchase funnel. Generally speaking, we distinguish firm-initiated contacts (FICs) from customer-initiated contacts (CICs). Traditionally, marketing communication activities have focused on pushing messages on to consumers (Shankar and Malthouse 2007). However, these FICs (defined as any contact with a customer that is initiated by the firm) are increasingly unwanted (e.g., Blattberg et al. 2008). In addition, unsolicited campaigns such as faxes or e-mails are progressively outlawed in many countries. In contrast to FICs, CICs are defined as any contact with a firm that is initiated by a customer or prospective customer (e.g., Bowman and Narayandas 2001). The Internet has empowered consumers to interact with companies on their own terms. Although the effectiveness of FICs might be diminishing, CICs show a lot of potential and have become a significant component of firms' marketing campaigns (e.g., Ghose and Yang 2009). Response rates for CICs are projected to be about 15 times higher than traditional FICs (Sarner and Herschel 2008) because they are based on customers' own queries and are hence considered far less intrusive (Shankar and Malthouse 2007). Taken together, the elasticity of CICs such as paid search advertising should be substantially higher than those of FICs. In our conceptual framework, the activities are as follows: *e-mail* campaigns, *catalog* mailing, and *flyer* and *fax* campaigns represent the traditional marketing communication activities focusing on pushing messages at consumers (FICs), whereas Google's *AdWords* represents the customer-initiated contacts. We augment these activities by *discounts* given to customers to control for price effects.

2.2. Channels and Purchase Funnel Stages

Depicted as level 2 in Figure 1, customers' channel preferences are likely to differ across alternative use situations, including the closeness of the customer to the purchase decision (e.g., Alba et al. 1997). The central idea of the "purchase funnel" is that customers move toward a purchase in a series of stages, including a cognitive (e.g., need recognition and information search), an affective (e.g., evaluation of alternatives), and, ultimately, a conative (purchase) stage. Although the implied hierarchy has been questioned for hedonic and low-involvement products (e.g., Vakratsas and Ambler 1999), Inofec believed it was a useful starting point in the office furniture business. Currently, customers tend not to stay in one channel when moving through the funnel but switch between channels—cross-channel effects

Figure 1 Conceptual Framework



(e.g., Ahuja et al. 2003). Moreover, various feedback effects between stages, channels, and activities may exist (e.g., Ilfeld and Winer 2002). In our conceptual framework, the stages are as follows. For the online funnel, *Web visits* and *leads* (information requests) signal the beginning of the thought process (cognitive stage). *Request for quotes* (*via the website*) indicates that the prospective customer is evaluating the offer (affective stage). Finally, *orders* (*via the website*) is a straightforward variable representing the conative stage. For the off-line funnel, the variables are similar except that we do not observe an equivalent measure to Web visits.

2.3. Marketing Effects on Purchase Funnel Stages

Both online and off-line marketing activity may ultimately generate profits (level 3 in Figure 1) by inducing prospective customers to start and finish their purchase process either online or off-line. As for marketing effects on different stages of the purchase funnel, prior research offers two different perspectives. First, impersonal marketing communication activities may simply "feed the funnel," i.e., bring in prospective customers. In contrast, the second perspective posits that marketing communication activity effects may linger in the customer's mind and have a direct effect on later stages in the purchase funnel (e.g., Fulgoni and Mörn 2009). For instance, a "billboard" effect of paid search advertising (i.e., exposure to paid advertising increases the user's familiarity with the brand or firm name) might lead to more quotes or purchases for a highly exposed supplier. In addition, an "inferred quality" effect may exist: high levels of marketing communications may serve as a signal for unobservable product or service quality (e.g., Vakratsas and Ambler 1999). In our framework, we account for both: marketing activities affect the beginning but also later stages of the purchase funnel.

3. Data

Inofec sells office furniture products mostly to business customers. We use daily data from Inofec spanning January 2007–May 2009 as the model estimation period (and June–August 2009 as the experimental period) comprising four databases (i.e., transaction, marketing, online and off-line activities). The analysis is at the daily level because marketing actions vary daily, and we aim to distinguish the (cross) effects within the purchase funnel, which may occur within days. Our data cover 876 days (more than 2 and 1/2 years) and more than 12,000 customers for marketing activities and purchase funnel metrics across online and off-line channels, making it uniquely suited to address Inofec's management problem. Table 1 displays the variable operationalization.

We operationalized sales as revenues because unit sales are not informative as a result of vastly different prices (from €5.50 for a pencil-holder to more than €9,000 for a customized solution). Gross profits (i.e., profits before marketing) are the customer-individual revenues per order minus the customer-individual costs of goods sold (COGS) per order, aggregated

Table 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
	e-mail	Daily number of net e-mails (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
Off-line funnel	*Off-line leads*	Daily requests for information received via sales reps, telephone, or mail
	Off-line quotes	Daily requests for offers received via sales reps, telephone, or mail
	Off-line 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

across customers for each day. Our rationale for aggregating rather than considering customer-specific orders are as follows. First, Inofec's business is such that it requires an instream of new customers, for which customer-specific information is not readily available. Likewise, customer-specific data on Google AdWords click-through and early funnel metrics are not available. Finally, Inofec wanted to focus on aggregate profit effects first to make overall reallocations among marketing budgets, themselves readily available only at the aggregate level. Table 2 displays

Table 2 Descriptive Statistics for the Variables Used in the Analysis (per Day)

Variable	Mean	Median	Std. dev.
Catalog (€)	158.77	0	1,447.03
Fax (€)	51.98	0	429.44
Flyers (€)	828.03	0	2,901.11
AdWords (€)	148.84	151.89	28.87
E-mail (number of)	350	0	1,784.22
Discounts (%)	6.88	7.00	5.55
Web visits (number of)	584.24	578.00	277.33
Online leads (number of)	3.35	3.00	2.50
Online quotes (number of)	0.97	0	1.45
Online orders (number of)	13.06	11.00	12.25
Off-line leads (number of)	1.59	0	2.64
Off-line quotes (number of)	2.52	2.00	2.68
Off-line orders (number of)	38.12	41.00	29.89
Sales revenues (€)	30,063.00	29,277.00	28,856.78
(*Gross*) *profit* (€)	13,778.31	13,894.52	12,332.23

the mean, median, and standard deviation of the variables.

Among the marketing communication activities with cost information, flyers represent 70% of the total marketing cost, followed by catalogs (13%), Google AdWords (13%), and finally faxes (4%). These marketing activities amount to 6%, 1%, 1%, and 0.4%, respectively, of gross profits. The funnel metrics show that the online channel is more popular for information requests (online leads are higher than off-line leads) but that the off-line channel is more popular for quote requests and orders. In addition, the average off-line order (€286) is slightly higher than the average online order (€235). Finally, gross profits represent 46% of sales revenues.

4. Methodology

We address the challenges of "click attribution" (i.e., customer click-through may be driven by off-line marketing spending) as well as cross-channel, direct, and feedback effects by extending the persistence modeling approach (Dekimpe and Hanssens 1999). We incorporate the five steps outlined in Table 3.

First, we determine *which variables* should be included in the model as endogenous, because they are Granger-caused by the other variables. Second, unit root and cointegration test tests reveal *in what form* the endogenous variables enter the model. Based on the first two steps, we can specify and estimate a dynamic system model of the dynamic interactions among endogenous variables. We estimate a vector-autoregressive (VAR) model including both online (Google AdWords, e-mail) and off-line (fax, flyer, catalog, and discounts) *marketing*, *online* purchase funnel metrics (Web visits, online leads, quote requests, and orders), *off-line* purchase funnel metrics (off-line leads, quote requests, and orders), and *profits* (revenues—costs of goods sold). All variables are endogenous, and hence we capture direct, indirect, and feedback effects of marketing communication activities on funnel stages. As control variables, we include an intercept C, a time trend T, day-of-week seasonal dummies (using Friday as the benchmark), and dummies for holidays. Equation (1) presents this model in matrix form, and the electronic companion displays all 14 equations in the model:

$$Y_t = A + \sum_{i=1}^{p} \Phi_i Y_{t-i} + \Psi X_t + \Sigma_t, \quad t = 1, 2, \ldots, T, \quad (1)$$

where A is a 14×1 vector of intercepts, Y_t is the 14×1 vector of the endogenous variables, and X_t the vector of exogenous control variables listed above, and Σ_t is the 14×1 matrix of residuals. Although this model yields unit profit effects of key interest to Inofec, we also want to compare the sales elasticities

Table 3 Overview of Methodological Steps

Methodological step	Relevant literature	Research question
1. *Granger causality tests*	Granger (1969) Trusov et al. (2009)	Which variables are temporally causing which other variables?
2. *Unit root and cointegration tests*		
Augmented Dickey–Fuller Test	Enders (2004)	Are variables stationary or evolving?
Zivot–Andrews test	Zivot and Andrews (1992)	Are unit root results robust to unknown breaks?
Cointegration analysis	Johansen et al. (2000)	Are evolving variables in long-run equilibrium?
3. *Model of dynamic interactions*		
Vector autoregressive model	Dekimpe and Hanssens (1999)	How do performance and marketing interact in the long run
VAR in differences	Bronnenberg et al. (2000)	and short run, accounting for the unit root and
Vector error correction model	Pauwels et al. (2007)	cointegration results?
4. *Policy simulation analysis*		
Unrestricted impulse response	Pesaran and Shin (1998)	What is the net dynamic impact of a marketing change on
Cumulative marketing elasticity	Pauwels et al. (2002)	performance?
Restricted policy simulation	Pauwels (2004)	What is the direct dynamic impact of a marketing change, controlling for its indirect effects?
5. *Validation analysis*		
VAR lag specification	Ventzislav and Lutz (2005)	Are the results robust to the lag selection criterion?
Regression analysis	This paper	Do the key results replicate in regression analysis?
Field experiment	This paper	Do the key results hold for a major policy change?

with previous research. To this end, we estimate a second VAR model, replacing profits with sales revenues. Elasticities are calculated from these unit effects (e.g., Trusov et al. 2009); we find for both models that the linear specification outperforms the log–log specification (similar to the findings for the daily data in Rutz and Bucklin 2011). The fourth step quantifies the effect of a change to marketing on performance, and the fifth step verifies that these effect estimates hold up, for example, in a field experiment. Moreover, we adapt restricted impulse response function analysis (Pauwels 2004) to separate the indirect effects of marketing activities (e.g., Google AdWords increase online quote requests, which in turn increases online orders) from direct effects (e.g., Google AdWords directly increases online orders). In the fifth step (detailed in the electronic companion), we validate our findings.

5. Key Results

Based on Granger causality tests (Granger 1969), unit root tests, and diagnostic tests for descriptive models (Franses 2005), we estimated both VAR models with all variables in levels (as depicted in Equation (1)) and one lag (as suggested by all four information criteria).[1] The models explain 77% of the variation in profits (adjusted $R^2 = 0.76$) and 78% (adjusted $R^2 = 0.78$) in revenues.

Based on the VAR estimates, we calculate the impulse response of performance to a one-unit change in the marketing variable, and we display both the long-term profit (unit) effect and its sales (revenues) elasticity in the first two columns of Table 4. *Catalog* had no significant effect and is therefore omitted. *Flyers*, the activity that consumes 70% of the marketing budget, brings in less money than it generates. This finding contrast with that of faxes and of e-mail, whose profit impact of €0.71 each is less than what the company estimates it spends per e-mail. Interestingly, the sales elasticities of these three marketing actions are consistent with that of off-line advertising reported in meta-analyses of approximately 0.05–0.10 (e.g., Tellis 2009).

In contrast, Google AdWords is estimated to yield €55.72 for each Euro spent. This estimate is 17 times higher than the estimated profit effect of faxes, the most effective off-line activity. This difference resembles the projected 15 times higher response rates of CICs versus FICs (Sarner and Herschel 2008). The sales elasticity of Google AdWords is 4.35, a lot higher than that of FIC elasticities reported in literature but similar to that of distribution (e.g., 2.42 in Srinivasan

Table 4 Marketing's Total Profit Effect, Sales Elasticity, and Its Timing in Days

Variable	Profit effect	Sales elasticity	Wear-in	Wear-out	90% effect
Fax (€)	3.33	0.05	0	6	4
Flyers (€)	0.57	0.04	2	9	5
AdWords (€)	55.72	4.35	1	9	7
E-mail (each)	0.71	0.12	2	5	5
Discount (1%)	789	0.75	0	2	1

Notes. As in previously published VAR applications, we only accumulate the significant impulse response coefficients to arrive at the total, over time, profit impact. If none of the impulse response coefficients is significantly different from zero, the reported total effect is zero.

[1] Please see the electronic companion for the results on the effect timing of marketing activity, effect on purchase funnel stages, and the validation.

et al. 2010). We checked for the possibility that the AdWords effect might be related to the relatively low spending by (1) examining nonlinear effects (but did not find such evidence) and (2) experimenting with substantially increasing AdWords (see §6).

Our results for the effect on purchase funnel stages (for details, please see the electronic companion) shows that 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 off-line orders. In contrast, faxes and flyers obtain only 6% and 20%, respectively, of their profit impact from the "other" (i.e., online) channel.

6. Recommendations to the Firm and Field Experiment

The results of our analysis enable the company to plan appropriate strategic activities. Together with Inofec, we derived the following recommendations for Inofec's marketing strategy:[2] (1) *decrease* spending on flyers and (2) *increase* spending on AdWords. To gain further insights with respect to model-free evidence, we conducted a 2×2 field experiment running for three months (June–August 2009) with a base (no changes in the planned flyer campaigns) and low condition for flyer spending (cutting flyer spending by half) and a base and high condition for AdWords spending (doubling AdWords spending).[3] Any marketing activities other than flyers and AdWords were held constant during our experiment.

Recognizing that unobserved and uncontrollable factors might drive gross profit changes in the experimental period, Inofec agreed to a variation of difference-in-differences procedure[4] Next, we accounted for the difference in spending.[5] Table 5 shows the net profit changes. The average higher spending of €17.66 per day is more than offset by the higher profit changes—in either *Flyer* condition. Further, the average daily *Flyer* savings of €137 a day is substantially higher than the decrease in profits before marketing cost, consistent with our analysis.

Table 5 Net Profit Changes

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

Table 6 Long-Term AdWords and Flyer Effect Estimates for Each Experimental Group

			AdWords	
			High	Base
Flyers	Base	AdWords	59.30	50.23
		Flyer	0.57	0.34
	Low	AdWords	63.42	52.31
		Flyer	0.61	0.92

Summing up, the field experiment supports our assertions. Reallocating firm's budget toward online activities yields a substantial increase in profit after marketing costs. This profit increase stems from two sources: increased sales through higher spending on AdWords (gross profit increase > spending increase) and cost savings through lower spending on flyers (cost savings > lost gross profit). To test whether the magnitude of our estimates would still hold up after such as substantial policy change, we reestimated our model (with the exception of catalogs, which were not sent during the experiment) on the 91 days of data during the experiment, and we display the results in Table 6 for AdWords and flyers. We find that the long-term marketing effects for each experimental group are in the same order of magnitude as those reported before the experiment.

7. Organizational Impact

Our work has significant organizational impact[6] along several dimensions.

[2] Two more recommendations are to increase spending on faxes and e-mail campaigns. The first proved impractical because of new legal restrictions forbidding unsolicited fax campaigns introduced in the Netherlands (October 1, 2009). Moreover, Inofec considered it safe to increase e-mail campaigns because of our discussions and their own experience. While the frequency was not that high in the past, Inofec now sends a weekly e-mail to existing customers as well as people who have asked for information before or subscribed for receiving e-mails.

[3] We built four experimental groups based on regions in Inofec's home market (the Netherlands) for which we could vary both flyers and Google AdWords spending. These groups are comparable in terms of total customer spent (mean, €1099.26; std. dev., 105.39), recency (mean, 247.18; std. dev., 3.24), frequency (mean, 2.73; std. dev., 0.32), monetary value (mean, €324.30; std. dev., 15.45), and number of existing (mean, 993; std. dev., 26) and new customers.

[4] 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 we 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).

[5] We divided the increase or decrease in spending over the total experimental period by the number of days of that period (91 days). Total AdWords spending increased by €1,607, which makes an average daily increase in AdWords spending of €17.66. Total flyer spending decreased by €12,462, which makes an average daily decrease in spending of €137.

[6] For more details on the organizational impact, please see the electronic companion.

Cultural Impact. Inofec has been managed by intuition for many years. Hence, it is very unlikely to totally abandon the "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 to make their decisions. Moreover, 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). 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 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).

Strategic Impact. Our work enables Inofec to determine the activities in which the company was generating or losing money and plan appropriate strategic activities. 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 in a personal communication: "The power and effectiveness of our website and AdWords were surprising. Based on that, we have an increasing interest in investing in online activities." Our decomposition of marketing's profit impact 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 off-line activities, explicitly distinguish the effects, and explore new opportunities due to new technical developments" (personal communication).

8. Conclusion

In conclusion, our project served as a turning point for Inofec to abandon pure gut feeling and to use instead marketing science in order to gain competitive advantage and increase profit.[7] The approach's strategic, financial, operational, and cultural impacts have been significant. Our field experiment helped us and the firm testing the implementation and robustness of our recommendations. Although the specific focus of this paper is on Inofec BV, the need for accountability and practical marketing science tools to allocate one's marketing communication budget across media and online and off-line channels is not limited to our partner firm. As such, our journey with Inofec included several insights we believe are valuable across various settings. 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. In addition, 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 that has received little research attention. Our demonstration of the magnitude and direction of cross-channel effects may inspire other firms to perform their own analyses to overcome separate accountability for online and off-line marketing budgets and results. Finally, 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 the results and recommendations in a field experiment is new and may inspire further testing of when the Lucas (1976) critique presents a substantial empirical challenge to the model's recommendations.

Limitations of our approach inspire future research: we did not have data on competitive spending. Although this is typical for direct marketing applications (e.g., Rutz and Bucklin 2011), and competitive reaction is unlikely to strongly affect marketing effectiveness (Pauwels 2004), modeling competitive effects would add to our understanding of fluctuations in Inofec's marketing effectiveness and performance. The absence of competitive data also meant that we could not determine relative-to-competition elasticities, which are key in formal optimization models (Gupta and Steenburgh 2008). Moreover, although we did conduct a field experiment to validate the direction of our recommendations, we did not have the opportunity to optimize marketing spending given the very high estimated elasticity of AdWords. Evidently, increasing AdWords must eventually yield diminishing returns, which we did not find in our data. Continued experimentation will help us discover the upper and lower bounds on different mix variables. In doing so, one can also test when to spend on which activity (i.e., media pulsation) to further improve marketing effectiveness.

9. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://mktsci.pubs.informs.org/.

[7] For more details on the transferability, please see the electronic companion.

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