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Managing Blood Donations with Marketing

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Blood banks rely on marketing to encourage donors to give blood. Many, if not most, blood banks in the United States are community-based not-for-profit organizations with limited marketing budgets. As a result, blood banks increasingly use novel and inexpensive online media, i.e., *paid*, *owned*, and *earned* (POE) media, in their marketing efforts. We propose a dynamic model to help blood bank marketing managers understand how blood donations can be managed via online POE media. We analytically characterize the optimal forward-looking paid media strategies, taking into account the asymmetric costs related to shortage and excess of blood, as well as the possibility of a cost-free target donation zone. We detail new advertising resource allocation rules for blood banks and show when traditional allocation recommendations do not apply. Additionally, we discover that under certain circumstances, owned/earned media activities hurt the blood bank's performance, despite being (predominantly) free. We validate our analytical model by using daily donation data from a community-based blood bank and measure the effects of POE media activities on the level of blood donated.

Keywords: blood bank; paid-own-earned media; social/non-profit marketing; optimal control; time series; Bayesian estimation; dynamic linear model
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1. Introduction

Demand for blood grows faster than blood donations. Because of aging populations, the demand for blood in developed countries rises by 6% to 8% annually, while donations increase by only 2% to 3%.[1] Blood collection, a not-for-profit activity conducted by blood banks, involves matching blood donations with blood demand. This task is challenging. First, blood banks do not control how hospitals use and order blood. Second, blood cannot be bought from donors (Hillyer et al. 2007) and no formal "blood market" exists where supply and demand determine a clearing price (Slonim et al. 2014). Finally, blood is perishable. In the United States 4.3% of collected units are discarded because they were not used before their expiration dates (Whitaker 2013). Marketing allows blood banks to address these challenges and help manage donations to avoid blood shortages, while minimizing costs due to outdated units.

Focusing on the demand for blood, the operations research literature has shown that a "first in, first out" inventory policy minimizes the number of outdated units and blood shortages (e.g., Nahmias 1982, Prastacos 1984, Pierskalla 2005). Meanwhile, research in information systems has focused on how information technology can help optimize blood use (Belien and Forcé 2012). To our knowledge, however, these two streams ignore the challenge of managing the supply of blood, i.e., attracting donors. Behavioral studies focus on the psychological barriers to blood donation, but abstract away from the challenge of collecting the right amount of blood (e.g., Pessemier et al. 1977, Burnett 1981, Nguyen et al. 2008). Thus, the extant literature on blood does not, to our knowledge, address the role of marketing in managing blood donations.

We aim to address this gap by investigating how blood banks can use marketing to manage blood donations. While the marketing literature has a long history of investigating media allocation rules, it is not clear that findings from sales or profit maximizing companies apply to the management of blood donations. Additionally, marketing managers at non-profit blood banks often face advertising budgets that restrict the type of marketing instruments at their disposal. Specifically, we investigate how inexpensive online paid, owned, and earned (POE) media (e.g., Corcoran 2009, Goodall 2009, Stephen and Galak 2012) can be leveraged to attract donors in lieu of traditional expensive mass media.

[1] http://www.schlitzpark.com/events/1562-american-red-cross-blood-drive. Last accessed on April 10, 2014.

To answer these questions and provide managerial guidelines on the management of POE media by blood banks, we frame the management of blood donations as a dynamic advertising resource allocation problem. We propose a dynamic model where the blood bank's POE media strategy drives the volume of blood collected (i.e., donated). Contrary to for-profit settings, our approach allows for an objective function that captures asymmetric costs between shortage and excess of blood in addition to a cost-free region.

We contribute to the marketing literature on several different dimensions. First, we establish that the inverse allocation rule found in the advertising literature (e.g., Erickson 2003) is optimal for blood banks only in shortage and excess situations, but not when donations are within the cost-free region. In that case, the optimal rule is to *increase* spending with donations. Second, we find that an increase in effectiveness of advertising instruments could cause the blood bank to spend *less* on these instruments and *not more* as prescribed by the extant integrated marketing communications (IMC) literature in for-profit settings (e.g., Naik and Raman 2003). Third, we show that POE media should be treated differentially in the blood donation management problem. More specifically, we find that despite being predominantly free, owned/earned media can hurt the blood bank because it cannot adjust how active these platforms are, i.e., these platforms cannot (and should not) be shut down quickly when donation levels are too high. Paid media, on the other hand, can be turned on/off easily to dampen donations, thus alleviating the risk of spoilage. Fourth, using data from a community blood bank we empirically measure the impact of POE media on blood donations.

We proceed as follows. First, we provide an overview on the U.S. blood supply and POE marketing. We then present our analytical model and derive novel allocation rules for the management of POE media for blood banks. Next, we empirically validate the proposed model in a Bayesian framework using a novel data set from a community blood bank. Finally, we conclude with a discussion of our key insights.

2. Research Background

2.1. The U.S. Blood Supply

Hundreds of blood banks exist in the United States. At one extreme, large establishments such as the New York Blood Center or the Puget Sound Blood Center collect thousands of daily donations and serve hundreds of hospitals. On the other end of the spectrum, small community-based centers such as LifeStream in California or Suncoast Communities Blood Bank in Florida collect only a few hundred pints a day and serve a handful of local hospitals. Collectively, blood banks deliver on average 15 million units of blood (supplied by donors) to over 4,000 hospitals across the United States (Whitaker et al. 2011).

Before the 1970s, U.S. blood banks paid donors for blood. The new U.S. blood policy that arose under Nixon's presidency required U.S. blood banks to label blood units collected from paid donors (Lyons 1971, Drake et al. 1982, Hillyer et al. 2007). Blood banks then ceased recruiting donors via monetary incentives. Consequently, marketing communications became critical in the management of blood donations. The advent of online media enabled blood banks to reach donors without having to invest in costly mass media advertising.

2.2. POE Marketing

Before the Internet, marketers were restricted to either expensive advertising media such as TV or print, or methods that do not scale well such as interpersonal communications (e.g., personal selling). The Internet changed this landscape by allowing inexpensive one-to-many (advertising) communication, as well as scalable one-to-one interactions. These new media outlets are referred to as POE media (see Corcoran 2009, Goodall 2009, Stephen and Galak 2012).

Paid media usually refers to paid online media. The biggest and most effective of these is paid search advertising, which organizations use to address individuals directly during their electronic search. Its pay-per-click model differs from the pay-per-exposure model of traditional advertising. A blood bank benefits from paid search advertising due to the relatively inexpensive nature of this instrument and its ability to intercept a potential donor during her search for blood donation options. *Owned* media refers to content that belongs to the organization, for example, the own website, a blog, or the presence on social media sites such as Facebook or YouTube. Last, *Earned* media refers to mentions of the brand not generated by the organization, e.g., comments on Facebook by donors. Paid and, in part, owned media are most similar to the traditional marketing tools such as advertising, branding, or corporate identity (e.g., store or catalogue design). However, earned media are truly novel in that they allow consumers to broadcast their opinions effortlessly to a much larger audience than was possible at any time before the Internet. Thus, marketing managers must understand how to leverage earned media to their advantage to circumvent the typically limited marketing budgets of non-profit organizations.

Substantially, this study contributes to the nascent literature on POE media. In particular, we build on Stephen and Galak's (2012) work that shows a significant impact of online earned media on the lending volume in a microlending marketplace. We generalize this research by simultaneously considering POE media and by deriving POE media allocation rules from our analytical modeling framework. The fundamental nature of earned media complicates its role in the modern marketing mix as it is generated by consumers and not by the organization. As such, the level of control exerted by the organization is *lower* compared to traditional marketing mix instruments, which inevitably impact the actions taken by the manager. The lower level of control on earned and, to some extent, owned media could have an adverse effect on the blood donation management problem, especially in the case of sustained high levels of donations that increase the risk of spoilage. In §3, we study how blood banks should use relatively inexpensive POE media to drive blood donations.

3. Managing Blood Donations with POE Media

We conceptualize POE media as follows. *Paid* media (u_P) are "pay for performance" media that can be adjusted easily and quickly, making them flexible, albeit potentially costly. Ease of adjustment makes paid media prime marketing instruments for blood banks in terms of balancing blood donations and local blood demand. *Owned* (u_O) and *earned* (u_E) media, however, are characterized by bigger, often infrequent, investments. The main advantage of these two types of media is that the marginal costs of generating additional exposures or clicks are close to zero. For example, costs to set up/rebuild a website or establish a presence on Facebook could be high, but the cost for an additional view, comment, or like is negligible. This advantage, however, comes at a price, which is their inherent inflexibility, i.e., they cannot be increased or reduced at will. Thus, whereas paid media can be easily used to manage daily fluctuations in blood donations, owned/earned media cannot. Next we link the level of donations to these marketing instruments.

Specifically, let $D(t)$ denote the level of blood donations at time t. We assume that each media type contains several instruments, i.e., for paid (P), owned (O), and earned (E) media we have the following set of options, i.e., $u_P = \{u_{P1}, \ldots, u_{Pi}, \ldots, u_{PP}\}$, $u_O = \{u_{O1}, \ldots, u_{Oj}, \ldots, u_{OO},\}$, and $u_E = \{u_{E1}, \ldots, u_{Ek}, \ldots, u_{EE}\}$. The change in the level of blood donations at time t is then given by

$$dD = \left(\sum_{i=1}^{P} \beta_{Pi}\sqrt{u_{Pi}(t)} + \sum_{j=1}^{O} \beta_{Oj}\sqrt{u_{Oj}(t)} + \sum_{k=1}^{E} \beta_{Ek}\sqrt{u_{Ek}(t)} - \delta D(t)\right) dt + dW, \quad (1)$$

with $D(0) = D_0$ and where β_{Pi} is the effectiveness of paid media i, β_{Oj} the effectiveness of owned media j, and β_{Ek} the effectiveness of earned media k. The term δ represents the decay rate of past donations and $1-\delta$ the carryover effect; finally, dW is the increment of a Brownian motion. Equation (1) extends the Nerlove and Arrow dynamic advertising model (Nerlove and Arrow 1962) to incorporate owned and earned media activities along with paid media. This model is commonly used in advertising research (see Table 1 in Aravindakshan and Naik 2011) and was previously extended to multiple media (e.g., Bass et al. 2007).

A blood bank's objective is to maintain the level of collected blood within a range that prevents both shortage and excess. While the cost implications of a shortage are straightforward (e.g., decreased quality of care, increased hospitalization days due to postponed surgeries, etc.), the cost implications of an excess are also substantial. First, collecting and storing blood is expensive and these costs cannot be recouped if the blood is ultimately discarded. Second, turning donors away when inventory is high could result in these donors never returning. Being turned away could serve as a permanent psychological excuse for not giving blood anymore (e.g., Prastacos 1984, Pillavin 1987, Halperin et al. 1998). Third, blood banks also provide information on how much blood is discarded, which can impede donors' willingness to give blood (and/or donate money). Finally, even though both shortage and excess of blood are costly to the blood bank, a shortage is more undesirable than excess (e.g., Brodheim and Prastacos 1979, Cohen and Pierskalla 1979).

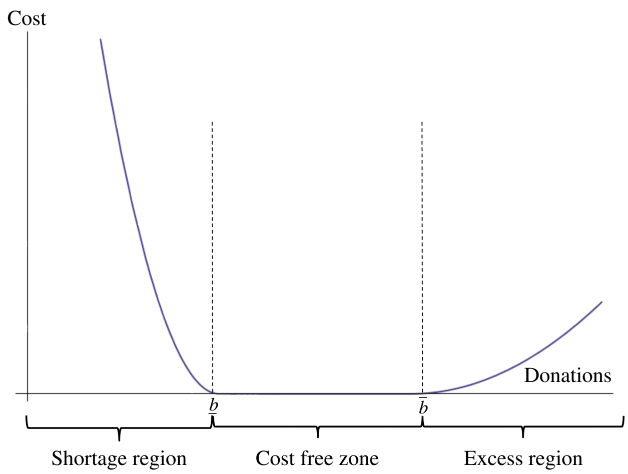
We capture these asymmetric costs using a novel loss function. Let $C(D(t))$ be the loss function that penalizes the shortage or excess of blood

$$C(D(t)) = \begin{cases} q_S(D(t) - \underline{b})^2 & \text{if } D(t) < \underline{b} \\ 0 & \text{if } \underline{b} \le D(t) \le \bar{b} \\ q_E(D(t) - \bar{b})^2 & \text{if } D(t) > \bar{b}; \end{cases} \quad (2)$$

where q_S and q_E capture the different costs associated with blood shortage and blood excess, respectively, while the interval $[\underline{b}; \bar{b}]$ delineates the cost-free zone determined by the demand for blood and its perishability (see Figure 1 for a graphical representation). The lower bound, i.e., $\underline{b}$, is determined by a demand that is too high such that it exposes the blood bank to the risk of shortage. On the other hand, the upper bound, i.e., $\bar{b}$, is determined by a demand that is too low compared to the blood bank's inventory, which means that the blood bank will have to discard blood due to its perishability if it exceeds this threshold.

As the forward-looking manager allocates resources to paid media to avoid shortage or excess of

Figure 1 (Color online) Blood Bank's Cost Function



blood, the blood bank's objective combines (2) with the amount invested in paid media, i.e., $\sum_{i=1}^{P} u_{Pi}$. The blood bank thus minimizes the objective function in (3)

$$J(D) = \min_{u_p} E\left[\int_0^\infty e^{-rt}\left\{C(D(t)) + \sum_{i=1}^{P} u_{Pi}\right\} dt\right], \quad (3)$$

subject to (1) to obtain its optimal POE media strategy, where $u_P = \{u_{P1}, \ldots, u_{PP}\}$. The term r gives the discount factor and $J(\cdot)$ is the blood bank's value function. We characterize the optimal strategy in each region and derive the following proposition:

Proposition 1. *The blood bank's optimal paid media strategy is*

$$u_{Pi}(D)^* = \left(\max\{0; \tilde{u}_{Pi}(D)/2\}\right)^2, \quad (4)$$

with

$$\tilde{u}_{Pi}(D) = \begin{cases} \beta_{Pi}(A_1 D + A_2) & \text{if } D < \underline{b} \\ \beta_{Pi}(B_1 D + B_2) & \text{if } \underline{b} \le D \le \bar{b} \\ \beta_{Pi}(C_1 D + C_2) & \text{if } D > \bar{b}, \end{cases} \quad (5)$$

where $A_1 < 0$ and $C_1 < 0$, while $B_1 > 0$.

Proof. See Online Appendix I (available as supplemental material at http://dx.doi.org/10.1287/mksc.2014.0892). □

Dynamic advertising models prescribe inverse allocation rules, i.e., to decrease spending as the target variable increases (e.g., Erickson 2003). We find that in our setting this recommendation holds only for the shortage and excess regions, but not for the cost-free zone. Indeed, Equation (5) reveals that when $D \in [\underline{b}; \bar{b}]$, $\partial u_{pi}(D)^*/\partial D > 0$, implying an increase in spending on paid media as the level of donations increases, i.e., a proportional spending rule. This outcome is driven by two mechanisms. First, the dynamic shadow price (measuring the sensitivity of the value function to marginal variations in donation levels) increases as the level of donations (the metric informing the media allocation decision) increases. Second, by implementing this strategy, the level of donations rapidly moves away from the shortage region, because, at the equilibrium, the growth of donations rapidly increases as $dD^*/dt > 0$ and $d^2D^*/dt^2 > 0$.

To clarify how the existence of a cost-free zone and asymmetric costs between shortage and excess of blood change the advertising policies, we report the optimal paid media strategy for three scenarios in Figure 2. In Panel A, we consider a symmetric loss function and no cost-free zone (i.e., $q_S = q_E$ and $\underline{b} = \bar{b} = b$). In this case, the cost of shortage and excess are identical. The optimal strategy is linearly decreasing in the level of donations, i.e., spending on paid media decreases as the level of donations increases. In Panel B, we consider an asymmetric loss function and no cost-free zone (i.e., $q_S > q_E$ and $\underline{b} = \bar{b} = b$). Note that in this case, the optimal policy is again to spend less on paid media as the level of donations increases. However, two differences emerge. First, the optimal policy becomes piecewise continuous with a jump at b. Second, the slope of the optimal strategy is steeper for $D < b$ than for $D > b$. Intuitively, this is driven by the fact that the cost of shortage is higher than the cost of excess (i.e., $q_S > q_E$). Finally, in Panel C, we report the optimal policy with an asymmetric loss function incorporating a cost-free zone (i.e., $\underline{b} < b < \bar{b}$, together with $q_S > q_E$). We find that within the cost-free zone, a proportional allocation rule is optimal.

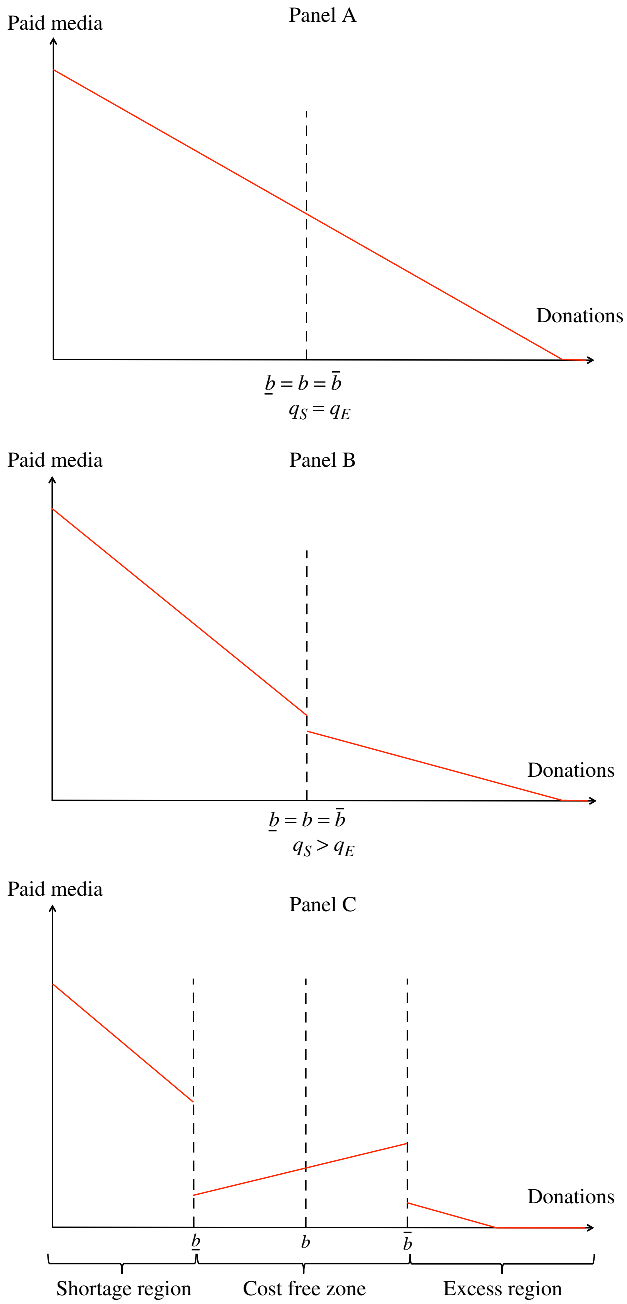
Proposition 2. *Own (Paid) Media Effect, i.e., $\partial u_{Pi}(D)/\partial \beta_{Pi}$*

- *In the shortage region,*
  - *if $\partial A_2/\partial \beta_{Pi} > 0$, then $\partial u_{Pi}(D)/\partial \beta_{Pi} > 0$.*
  - *If $\partial A_2/\partial \beta_{Pi} < 0$, then $\partial u_{Pi}(D)/\partial \beta_{Pi} > 0$ when $D < \tilde{D}_S$ and negative otherwise, where $\tilde{D}_S$ is a function of parameters.*
- *In the excess region,*
  - *if $\partial C_2/\partial \beta_{Pi} > 0$, then $\partial u_{Pi}(D)/\partial \beta_{Pi} > 0$.*
  - *If $\partial C_2/\partial \beta_{Pi} < 0$, then $\partial u_{Pi}(D)/\partial \beta_{Pi} > 0$ when $D < \tilde{D}_E$ and negative otherwise, where $\tilde{D}_E$ is a function of parameters.*
- *Finally, in the cost-free region,*
  - *if $\beta_{Pi}^2 < \sum_{h \ne i} \beta_{Ph}^2$, then $\partial u_{Pi}(D)/\partial \beta_{Pi} > 0$ if $D > \kappa/\delta$ and negative otherwise.*
  - *If $\beta_{Pi}^2 > \sum_{h \ne i} \beta_{Ph}^2$, then $\partial u_{Pi}(D)/\partial \beta_{Pi} > 0$ if $D < (\sum_{j=1}^{O} \beta_{Oj}\sqrt{u_{Oj}} + \sum_{k=1}^{E} \beta_{Ek}\sqrt{u_{Ek}})/\delta$ and negative otherwise.*

Proof. See Online Appendix I.

Proposition 2 shows that in every region, an increase in the effectiveness of paid media i may lead to decreased spending in this media. This insight contributes to the marketing literature, which in traditional for-profit settings, advises managers to always spend more when the effectiveness of a

Figure 2 **(Color online) Optimal Paid Media Strategy Under Different Scenarios**



marketing instrument increases. In all three regions, $\partial u_{Pi}(D)/\partial \beta_{Pi} < 0$ holds when two conditions are met. In the shortage and excess regions, the first condition pertains to the effect of increased effectiveness on the intercept of the advertising policy, ($\partial A_2/\partial \beta_{Pi}$ and $\partial C_2/\partial \beta_{Pi}$, respectively), whereas in the cost-free region the first condition pertains to the relative effectiveness of media i with respect to other media ($\beta_{Pi}^2 > \sum_{h\neq i} \beta_{Ph}^2$). In all regions, the second condition is defined by different thresholds for donations, i.e., $\tilde{D}_S$, $\tilde{D}_E$, and $(\sum_{j=1}^{O} \beta_{Oj}\sqrt{u_{Oj}} + \sum_{k=1}^{E} \beta_{Ek}\sqrt{u_{Ek}})/\delta$, in the shortage, excess, and cost-free regions, respectively. Thus, $\partial u_{Pi}(D)/\partial \beta_{Pi} < 0$ is driven primarily by the blood bank's objective, which is to ensure a target level (or range) of donations and not to maximize the volume of blood collected. Next, we investigate cross (paid) media effects.

Proposition 3. *Cross (Paid) Media Effect, i.e.,* $\partial u_{Pi}(D)/\partial \beta_{Ph\neq i}$

- *In the shortage region,*
  - *if* $\partial A_2/\partial \beta_{Ph\neq i} > 0$, *then* $\partial u_{Pi}(D)/\partial \beta_{Ph\neq i} > 0$.
  - *If* $\partial A_2/\partial \beta_{Ph\neq i} < 0$, *then* $\partial u_{Pi}(D)/\partial \beta_{Ph\neq i} > 0$ *when* $D < -(\partial A_2/\partial \beta_{Ph\neq i})/(\partial A_1/\partial \beta_{Ph\neq i})$ *and negative otherwise.*
- *In the excess region,*
  - *if* $\partial C_2/\partial \beta_{Ph\neq i} > 0$, *then* $\partial u_{Pi}(D)^*/\partial \beta_{Ph\neq i} > 0$.
  - *If* $\partial C_2/\partial \beta_{Ph\neq i} < 0$, *then* $\partial u_{Pi}(D)/\partial \beta_{Ph\neq i} > 0$ *when* $D < -(\partial C_2/\partial \beta_{Ph\neq i})/(\partial C_1/\partial \beta_{Ph\neq i})$ *and negative otherwise.*
- *Finally, in the shortage region,* $\partial u_{Pi}(D)/\partial \beta_{Ph\neq i} > 0$ *if* $D < (\sum_{j=1}^{O} \beta_{Oj}\sqrt{u_{Oj}} + \sum_{k=1}^{E} \beta_{Ek}\sqrt{u_{Ek}})/\delta$ *and negative otherwise.*

Proof. See Online Appendix I.

It follows from Proposition 3 that even in *the absence of direct interactions* between media, variations in the effectiveness of paid media h inform the optimal investment in paid media i. This finding departs from the extant literature in marketing resource allocation, which would have recommended not changing the allocation to media i when $\beta_{Ph\neq i}$ varies (i.e., $\partial u_{Pi}(D)/\partial \beta_{Ph\neq i} = 0$). This interdependence in media spending, despite the lack of direct interaction, is driven by the indirect effect of media h on media i that originates from the shadow price of donations and not through instantaneous profits as in Naik and Raman (2003). Last, we investigate the effect of owned and earned media on the value function of the blood bank or, in other words, their impact on the blood bank's long-term performance.

Proposition 4.

- *In the shortage region, an increase in owned/earned media increases the blood bank's value function when* $D < -(\partial A_3/\partial v)/(\partial A_2/\partial v)$ *if* $\partial A_3/\partial v > 0$, *where* $v = \{u_{Oj}, u_{Ek}\}$. *Otherwise, the value function decreases.*
- *In the excess region, an increase in owned/earned media increases the blood bank's value function when* $D < -(\partial C_3/\partial v)/(\partial C_2/\partial v)$ *if* $\partial C_3/\partial v > 0$, *where* $v = \{u_{Oj}, u_{Ek}\}$. *Otherwise, the value function decreases.*
- *In the cost-free region, the sensitivity of the value function with respect to media* $v = \{u_{Oj}, u_{Ek}\}$ *equals* $\partial J/\partial v = -2(r+2\delta)(D\delta - v)/((\sum_i \beta_{Pi}^2)\delta) + g(D, v)$, *which could be positive or negative.*[2]

[2] The function $g(D, v)$ is a nonlinear function of D, owned and earned media, as well as the model's parameters. We do not report $g(D, v)$ due to its long mathematical expression. We conducted numerical simulations to verify that both $\partial J/\partial v < 0$ and $\partial J/\partial v > 0$ can happen.

Proof. See Online Appendix I.

Proposition 4 provides conditions under which owned and earned media negatively affect the value function (i.e., long-term performance) of the blood bank. Similar to Propositions 2 and 3, the impact of owned and earned media on the value function depends not only on the region that donations are in (e.g., excess or shortage) but also on thresholds specific to each region. Therefore, Proposition 4 suggests that owned and earned media can be costly, despite the fact that the exposures generated are predominantly free, because the value function can decrease when owned and earned media increase. To understand the intuition behind this result, note that the blood bank can instantly adjust the level of paid media. Conversely, changes in owned and earned media are generally less frequent and less reactive to daily donation levels. For example, the blood bank would be ill-advised to take its website (owned) offline when the level of donations is too high. Apart from an immediate (and desired) impact on donations, there might be undesired consequences. For example, donors might assume that the blood bank is closed as the website is not accessible. As a result donors may not consider the blood bank for future donations. However, if the blood bank stops paid media, donors are unlikely to conclude that the blood bank is out of business.

To summarize, our results indicate that successful POE media strategies for a blood bank go beyond investing in paid media and capitalizing on owned and earned media. Our proposed allocation rules depart from the insights derived for profit-maximizing firms. In particular, we find that allocation rules in for-profit settings do not directly apply to blood banks. We also find that owned and earned media can have negative effects on the value function, i.e., the long-term performance, of the blood bank, despite the fact that they are predominantly free. Next, we provide an empirical illustration of our approach.

4. Data Description

Using donation and POE media data from a community blood bank we test the implications of the theoretical model and illustrate its normative results. The annual operating budget of the blood bank is \$48 million and it collects, on average, 50,000 units of blood per year to supply nine local hospitals.[3] Our data spans 318 days. During that time, the blood bank collected, on average, 157 pints of blood per day, with a minimum of 44 pints and a maximum of 318 pints. The proportion of pints discarded due to passed expiration dates is comparable to the national average with the objective to reach zero outdated units. As a community-oriented non-profit, the blood bank does not have access to a large marketing budget and cannot invest in mass media, e.g., TV.[4]

Because of budget constraints typical for a small non-profit, the blood bank relies on novel and inexpensive POE media. Specifically, marketing resources are allocated to paid search advertising and social media platforms such as Facebook and YouTube. We follow the typology of Stephen and Galak (2012) to classify the blood bank's online media into POE media. We measure the blood bank's paid media activities by its paid search advertising metrics. On average, the blood bank spent \$2.38/day on its Blood Donation campaign; the average number of clicks was five. This level of spending comports with other studies on paid search advertising (e.g., Table 1 in Chan et al. 2011). The maximum amount spent on a single day was \$12.77 and the minimum was zero dollars (for six days). The Blood Donation campaign targets potential blood donors searching for blood banks on Google.[5] We measure owned media activity using multiple metrics, i.e., the number of daily views on YouTube, the number of unique daily users on YouTube, and the number of daily page views on Facebook from users logged into Facebook.[6] Last, we measure earned media activity by the number of likes and unlikes on the blood bank's Facebook page and the number of daily comments on the blood bank's Facebook page. Table 1 summarizes the descriptive statistics for the variables in the data.

5. Empirical Analysis

5.1. Empirical Model

To estimate the parameters in (1) and illustrate its normative implications we discretize the donation

[3] The blood bank is part of a larger entity and thus is not required to file a Form 990 detailing its marketing budget.

[4] We collected data from the Form 990s of the top blood banks in the United States as provided by the Urban Institute based on total gross receipts. We found that larger blood banks have marketing budgets that vary from \$56,000 for the New York Blood Center at the low end to \$6,358,667 for the Gulf Coast Regional Blood Center at the high end; the median is \$501,206 and the mean is \$1,056,236. These figures show the wide variations in marketing budgets across blood banks.

[5] Note that the blood bank also ran a Blood Products and Services campaign targeting hospitals and pharmaceutical companies searching for blood products. As expected, we found that the Blood Products and Services campaign does not have a statistically significant effect on blood donations. Thus, we did not include the Blood Products and Services campaign data.

[6] Note that our data on owned media stem from content hosts (such as YouTube and Facebook) alone. The blood bank did not keep accurate logs of their own website visits. Because of this constraint we cannot include data on the blood bank's website visits.

Table 1 Descriptive Statistics

	Avg.	Std.	Min	Max
Number of daily donations	157.45	55.84	44	318
Paid media ($)				
Blood donation campaign	2.38	1.68	0	12.77
Owned media				
YouTube views	11.95	16.60	0	154
YouTube unique users	6.75	8.09	0	71
Facebook page views	12.66	9.59	0	82
Earned media				
Facebook new likes	2.84	3.11	0	31
Facebook new unlikes	0.36	0.64	0	3
Facebook new comments	3.19	5.03	0	35

dynamics to the daily level. Our empirical model is given by

$$D_t = \lambda D_{t-1} + \overbrace{\beta_1\sqrt{u_{P1t}}}^{\text{Paid media}} + \overbrace{\beta_2\sqrt{u_{O1t}} + \beta_3\sqrt{u_{O2t}} + \beta_4\sqrt{u_{O3t}}}^{\text{Owned media}}$$
$$+ \overbrace{\beta_5\sqrt{u_{E1t}} + \beta_6\sqrt{u_{E2t}} + \beta_7\sqrt{u_{E3t}}}^{\text{Earned media}} + \omega_t^D. \tag{6}$$

The level of donations in the current period, i.e., a day, is driven by the blood bank's POE media activities. Each donation corresponds to one pint of blood drawn from a donor, i.e., 450 milliliters of fluid per donation. Paid media metrics include the dollar amounts allocated to the Google Blood Donation campaign (u_{P1t}). Owned media metrics include YouTube views (u_{O1t}), YouTube unique users (u_{O2t}), and Facebook page views (u_{O3t}). Finally, earned media metrics include user activity on the blood banks owned media such as Facebook new likes (u_{E1t}), Facebook new unlikes (u_{E2t}), and Facebook new comments (u_{E3t}). The effectiveness of the POE media is measured by the parameters $\beta_1, \ldots, \beta_7$. We test whether POE media exhibit diminishing marginal effects on the level of donations by taking the square root and the logarithmic transformations of the actual observed value in our estimation procedure. We kept the square-root transformation as it provided the best fit.[7] From our discussions with the management of the blood bank we learned that the blood bank is a valued part of the community and has a group of loyal donors. To account for this, we include a carry-over effect in our model specification, i.e., a certain proportion (λ) of the previous period's donation level will occur in the current period without any marketing effort in the current period. This carryover (λ) captures the dynamic nature of the blood donation process. Finally, ω_t^D is a normally distributed error term.

5.2. Estimation Method

We use a Dynamic Linear Model (DLM) (West and Harrison 1997) implemented in a Bayesian framework to estimate the parameters of Equation (6). In marketing, DLMs have been used to address scenarios in which a key component of the data is unobserved (e.g., Bass et al. 2007), as is true in our model. An appealing feature of the DLM is that it simultaneously captures the dynamic evolution of the level of donations and the effects of POE media on donation dynamics.

Note also that it is potentially important to account for seasonality in donation activities. We include 0/1 indicator variables to account for day-of-the-week effects in blood donations ($Monday_t, \ldots, Friday_t$). Note that the blood bank is closed on Sundays and holidays. The parameters $\gamma_1, \ldots, \gamma_5$ measure the impact of the day-of-the-week on the level of donations. To estimate our model given in Equation (6), we define the required transition and observation equations. The *transition* equation is given by

$$D_t = (1-\delta)D_{t-1} + C_t + \omega_t^D, \tag{7}$$

where $C_t = \beta_1\sqrt{u_{P1t}} + \beta_2\sqrt{u_{O1t}} + \beta_3\sqrt{u_{O2t}} + \beta_4\sqrt{u_{O3t}} + \beta_5\sqrt{u_{E1t}} + \beta_6\sqrt{u_{E2t}} + \beta_7\sqrt{u_{E3t}}$. Next we link Equation (7) to the observed volume of blood collected via the *observation* equation

$$Y_t = ZD + \gamma_1 Monday_t + \gamma_2 Tuesday_t + \gamma_3 Wednesday_t$$
$$+ \gamma_4 Thursday_t + \gamma_5 Friday_t + \varepsilon_t. \tag{8}$$

We relate the estimated level of donations D_t from Equation (7) to the observed level of donations Y_t in Equation (8) through Z (where $Z=1$). We assume $\epsilon_t \sim N(0, \sigma_\epsilon^2)$.

Inference in the model given by Equations (7) and (8) could be biased. Sources for this bias could be simultaneity in the blood bank's decision making or an omitted variable bias related to owned and earned media, e.g., these metrics are high or low due to some unobserved external event. Finally, there could be a bias due to measurement error in owned and earned media as these are reported by third party firms and not directly measured by the blood bank. To alleviate concerns about these issues, we use an instrumental variables (IV) approach estimated in a seemingly unrelated regression (SUR) set-up. Compared to two-stages estimation procedures typically used in a frequentist setting, our Bayesian framework allows for simultaneous estimation of the model and the IV equations (e.g., Rossi et al. 2005).

[7] Note that one could have a potentially different conceptualization of diminishing marginal effects. Our approach assumes that diminishing marginal effects are media specific, i.e., additional paid media exposures do not affect the effectiveness of, e.g., earned media. We have tested a specification in which diminishing marginal effects are defined on the sum of the media exposure. For our data, our proposed specification given in (6) fits the data better (results are available from the authors on request). We want to thank an anonymous reviewer for this suggestion.

In our case, there is concern about all POE media, thus we use seven IV equations to address these potential endogeneity concerns. We describe our approach to paid media before we detail our instrumentation approach for owned and earned media. We use two sources of variation to instrument for paid media. First, we use the blood bank's shipment data as a source of external variation. The shipment data reflect a hospitals' blood demand that is not under the control of the blood bank. This is similar to IV approaches to price endogeneity using input (raw material) prices as instruments for the endogenous price. For example, Kuksov and Villas-Boas (2008) use tomato prices to instrument for price in a model of brand choice in the ketchup category. We also use lagged paid media to address concerns with the widely-used management practice of setting the current level of advertising based on the past level of advertising. Last, we use lagged cross media, i.e., lagged values of owned and earned media. As such, our IV equation for paid media is given by

$$u_{P1t} = \lambda_1^P u_{P1t-1} + \lambda_2^P u_{P1t-2} + \lambda_3^P S_{t-1} + \lambda_4^P S_{t-2} + \sum_{j=1}^{J} \lambda_{4+j}^P u_{Ojt-1} + \sum_{k=1}^{K} \lambda_{4+J+k}^P u_{Ekt-1} + \omega_t^P, \quad (9)$$

where S is shipment of pints of blood, $\lambda_1^P, \ldots, \lambda_{4+J+K}^P$ are parameters to be estimated, and ω_t^P is a normally distributed error term.

We instrument for owned and earned media using the following set-up for all owned and earned media. The data allows us to instrument with own lagged values as well as cross values for owned and earned media. For example, to instrument for u_{O1t} we use lagged values of u_{O1t} in addition to the lagged value of u_{O2t} and u_{O3t} as well as the lagged values of all earned media. For exemplary purposes we give the IV equation for the first owned media

$$u_{O1t} = \lambda_1^{O1} u_{O1t-1} + \lambda_2^{O1} u_{O1t-2} + \sum_{j=2}^{J} \lambda_{1+j}^{O1} u_{Ojt-1} + \sum_{k=1}^{K} \lambda_{1+J+k}^{O1} u_{Ekt-1} + \omega_t^{O1}, \quad (10)$$

where $\lambda_1^{O1}, \ldots, \lambda_{1+J+K}^{O1}$ are parameters to be estimated and ω_t^{O1} a normally distributed error term. The IV equations for the other owned and earned media follow the set-up of Equation (10). In addition, we test for exogeneity of the instrumented advertising metrics using the approach by Engle et al. (1983). We find that the instrumented advertising metrics satisfy the exogeneity requirement (Naik and Raman 2003, Sridhar et al. 2011; please see Online Appendix II). We estimate the model given by (7) and (8) and the seven IV equations by defining a correlation structure as follows: $(\omega_t^D, \omega_t^P, \omega_t^{O1}, \ldots, \omega_t^{O3}, \omega_t^{E1}, \ldots, \omega_t^{E3}) \sim N(0, \Omega)$, where Ω is a full (8×8) covariance matrix to be estimated. See Online Appendix III for a complete description of the estimation procedure nesting an SUR IV approach in a DLM framework.

6. Empirical Results

6.1. Fit and Forecasts

We investigate model performance based on in-sample fit as well as predictive performance out-of-sample. We find that the proposed dynamic model of blood donations fits the data well in-sample (marginal log-likelihood $= -2{,}670$). In comparison, a model without dynamics (only POE variables and days of the week estimated in a regression setting) fits the data worse (marginal log-likelihood $= -3{,}177$). Compared to a model without donation dynamics, the proposed model fits the data significantly better; the Bayesian factor differential is 507 points (greater than the critical difference of six, Newton and Raftery 1994). We conclude that in-sample fit favors a model accounting for donations dynamics.[8]

The proposed model's prediction accuracy is determined by re-estimating our model using the first 190 observations only.[9] Based on the set of parameter estimates, we calculate k-step[10] ahead of daily predicted values for observations not included in the estimation set. We find that the mean absolute percentage error (MAPE) of the 10-step ahead daily forecasts is 41%. Finally, we compare the out-of-sample performance of the proposed model to a model that includes the day of the week and the POE media without the donation dynamics. We find that when not allowing for donation dynamics the ability to correctly forecast the level of donation is greatly decreased (MAPE of 86% versus MAPE of 41% for our proposed model). We present the parameter estimates in Table 2.

6.2. Paid Media

We find that the Blood Donation paid search campaign (targeted toward potential donors) has a significant and positive effect on the level of donation,

[8] Additionally, we investigated the possibility of different carry-over effects per media using an Adstock approach estimated with a three-stage-least-squares procedure (e.g., Dinner et al. 2014). We find that, for our data, our proposed model provides a better fit (details are available from the authors on request). We want to thank the review team for this suggestion.

[9] We split the data 60/40. We have also tried different splits yielding similar results. Results are available from the authors on request.

[10] We present the results of a 10-step head forecast. Our results are robust to the number of steps, i.e., the proposed model with donations dynamics outperforms the model without dynamics for a wide variety of step sizes. Results are available from the authors on request.

Table 2 Empirical Results

Variable	Parameter estimates
Carryover Effect	**0.82** (0.71, 0.90)
Blood Donation Campaign (*P*)	**7.65** (1.17, 15.57)
YouTube Views (O_1)	2.93 (−17.10, 21.74)
YouTube Unique Users (O_2)	−0.40 (−9.40, 9.32)
Facebook Page Views (O_3)	−3.35 (−12.69, 6.31)
Facebook New Likes (E_1)	**16.92** (1.63, 33.07)
Facebook Unlikes (E_2)	−4.56 (−15.25, 7.02)
Facebook Comments (E_3)	3.99 (−2.54, 11.31)
Monday	**51.57** (32.29, 70.90)
Tuesday	**52.59** (33.18, 71.82)
Wednesday	**60.20** (40.75, 79.36)
Thursday	**40.92** (20.98, 61.12)
Friday	**30.65** (10.64, 50.40)

Note. Cell entries are posterior mean and 95% coverage intervals (in parentheses).

$\hat{\beta}_1 = 7.65$. The implied elasticity (at the mean) is 0.04, which is consistent with previous findings on advertising effectiveness (e.g., Ataman et al. 2008). Recent research on paid search advertising also supports its effectiveness as an instrument to drive clicks and sales (for example, see the chapter on paid search in Coussement et al. 2013). In the case of blood banks we speculate that paid traffic is the closest instrument to donation. Specifically, a consumer who has made up her mind to donate blood is looking for an outlet in her area. Paid (search) media allows the blood bank to directly address this potential donor and guide her to a collection site. In other words, paid (search) media provide a solution to the donor's wants and needs and are highly effective acquisition tools. Finally, there could also be a yellow-page effect in that a donor who knows about the blood bank will use a search engine to find it and responds to paid (search) media to gather the information needed to donate blood.

6.3. Owned Media

Owned media includes the blood bank's YouTube (u_{O1}, u_{O2}) and Facebook page views (u_{O3}). We first discuss the effect of YouTube page views. The blood bank has a YouTube channel and has posted videos on topics such as blood donations, the activities of the blood bank, and how donating blood helps to improve other people's lives. We summarize views across these types of videos in one metric, YouTube views. Additionally, we include a second measure capturing the number of unique users who view videos. We find that owned media activities on the blood bank's YouTube channel have no significant effect on donation levels (see Table 2; $\hat{\beta}_2$ and $\hat{\beta}_3$ are not significant). The same holds for Facebook page views. We speculate that simply viewing a Facebook page does not create enough engagement to donate blood immediately. For example, a casual visitor to the Facebook page might be simply collecting information. However, the Facebook page allows visitors to interact with the blood bank on a more active engagement level, i.e., by providing Facebook likes or leaving comments (which we classify as earned media and discuss next).

6.4. Earned Media

Facebook allows users to comment and express explicit preferences via a "like" or "unlike." We find that earned media activities measured by these Facebook metrics have a positive and significant effect on donation levels. First, the Facebook "like" metric has a positive and significant effect, $\hat{\beta}_5 = 16.92$ (elasticity of 0.05). "Likes" not only signal the intrinsic interest of potential donors towards the blood bank but also reveals their preferences to their social networks on Facebook. From the blood bank's perspective, a new "like" increases the blood bank's (brand) presence on Facebook, e.g., via the newsfeed. This could result in creating trust in the organization and its mission, potentially reducing the barriers to donations. We also find that the number of "unlikes" on a Facebook page (i.e., an individual removes a previous "like") has no impact on blood donation levels. This result might occur because "unlikes" are not communicated across the network, i.e., friends are not notified (e.g., via newsfeed) if a previously liked item is "unliked." Finally, we test for the impact of Facebook comments on blood donation levels. We found no significant effect on donations ($\hat{\beta}_7$).

6.5. Donation Carry-Over and Day-of-Week Effects

Table 2 reports the parameter estimates of the proposed model. We find a significant donation carry-over effect, $\hat{\lambda} = 0.82$, which indicates that marketing actions not only affect current levels of donations but also future donations. Moreover, we find that during the week (Monday–Friday), on average, the level of donations is higher compared to a Saturday (see

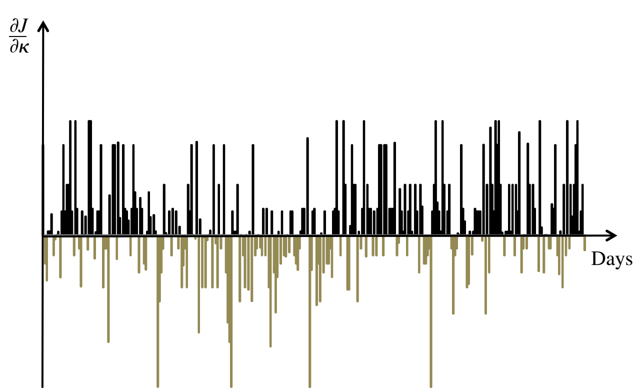
Table 2). The average level of donations for a weekday versus a weekend is about 47 pints higher.

6.6. Impacts of Owned and Earned Media on the Blood Bank

Based on these empirical results we investigate when owned and earned media affect the performance of the blood bank, as measured by its value function, $J(D)$. We compute $\partial J/\partial\kappa$, the sensitivity of the value function with respect to marginal variations of κ, the collective effect of owned and earned media on the number of blood donations, i.e., $\kappa = \sum_{j=1}^{O}\beta_{Oj}\sqrt{u_{Oj}} + \sum_{k=1}^{E}\beta_{Ek}\sqrt{u_{Ek}}$.

Differentiating the value function with respect to κ allows us to derive when owned and earned media positively (or negatively) affect the blood bank. Based on our discussions with the blood bank, we learned that it aims at an average target number of donations (b) of 140 pints. For exposition, we assume that the bounds of the cost-free zone are $\underline{b} = 0.90b$ and $\bar{b} = 1.2b$, that the discount rate is 5% per annum, and that the cost of shortage is three times the cost of excess. Normalizing the excess cost to one, we compute the sensitivity of the value function to marginal variations of κ over time. This results in novel insights. First we find that owned/earned media improve the blood bank's performance (in terms of the value function) on 199 days (out of 318), but are detrimental on the remaining days. This split (63% versus 37%) is obtained by counting the number of days where $\partial J/\partial\kappa > 0$ and where $\partial J/\partial\kappa < 0$. We also find that there are differences between regions. Indeed, we discover that, on average, the elasticity of the value function with respect to owned and earned media equals 1.55 in the shortage region, 0.99 in the cost-free region, and −0.19 in the excess in region. Figure 3 plots the sensitivity of the blood bank's value function with respect to owned/earned media over time.

Figure 3 (Color online) Sensitivity of the Value Function of the Blood Bank with Respect to O/E Media



7. Investigating POE Synergies

7.1. Paid Media Strategy in the Presence of Synergy

We complement our analytical and empirical findings to investigate synergistic effects between media.[11] For ease of exposition, we first investigate the role of synergy in a parsimonious normative model, where there is only one paid media, one owned media, and one earned media. In that case, Equation (1) becomes

$$\begin{aligned} dD = \big(&\beta_P\sqrt{u_P(t)} + \beta_O\sqrt{u_O(t)} + \beta_E\sqrt{u_E(t)} \\ &+ \gamma_{PO}\sqrt{u_P(t)}\sqrt{u_O(t)} + \gamma_{PE}\sqrt{u_P(t)}\sqrt{u_E(t)} \\ &+ \gamma_{OE}\sqrt{u_O(t)}\sqrt{u_E(t)} - \delta D\big)dt + dW, \end{aligned} \tag{11}$$

where γ_{PO} is the synergistic effect of paid with owned media, γ_{PE} is the synergistic effect of paid with earned media, and γ_{OE} is the synergistic effect between owned with earned media. We obtain the following proposition.

Proposition 5. *The blood bank's optimal paid media strategy when synergistic effects are present is*

$$u_P(D)^* = \big(\max\{0; \tilde{u}_P(D)/2\}\big)^2, \tag{12}$$

with

$$\tilde{u}_P(D) = \begin{cases} (\beta_P + \gamma_{PO}\sqrt{u_O} + \gamma_{PE}\sqrt{u_E}) \\ \quad \cdot (G_1 D + G_2) & \text{if } D < \underline{b} \\ (\beta_P + \gamma_{PO}\sqrt{u_O} + \gamma_{PE}\sqrt{u_E}) \\ \quad \cdot (H_1 D + H_2) & \text{if } \underline{b} \le D \le \bar{b} \\ (\beta_P + \gamma_{PO}\sqrt{u_O} + \gamma_{PE}\sqrt{u_E}) \\ \quad \cdot (I_1 D + I_2) & \text{if } D > \bar{b}, \end{cases} \tag{13}$$

where $G_1 < 0$ *and* $I_1 < 0$, *while* $H_1 > 0$.

Proof. See Online Appendix I.

The optimal paid media strategy, when synergistic effects are present, is qualitatively similar to Proposition 1, i.e., decreasing in the level of donations in both the shortage and excess regions and increasing in the level of donations in the cost-free zone. We also conducted sensitivity analyses to investigate whether the results from the IMC literature generalize in our setting. First, as synergies increase, should advertising spending increase? Second, if owned or earned media become more effective, should the advertising allocation change?

We find that, contrary to traditional recommendations, paid media spending should not always increase when synergistic effects increase since $(\partial u_P(D)/\partial\gamma_{PO})(\partial u_P(D)/\partial\gamma_{PE})$ could be both positive

[11] We thank the review team for this suggestion.

and negative, while $\partial u_P(D)/\partial\gamma_{OE}$ is always negative. At the same time, if owned and earned media increase, any increase or decrease in paid media spending depends on the respective levels of these media and model parameters. Finally, we find that when the main effect of owned and earned media increases, spending in paid media should decrease.

7.2. Estimating a Synergy Model

We also investigate empirically the existence of synergies in two different ways. First, we add all possible two-way media interactions to the model given by Equations (7) and (8). This results in seven main effects and 21 interaction effects. We call this the Full Synergy Model. In our setting we find that the interaction effects are highly correlated, raising concern about multicollinearity hampering the estimation results. We address these concerns using a variable selection approach. We use a stochastic search variable selection procedure ((SSVS), e.g., Trusov et al. 2010). The basic idea of SSVS is to leverage Bayesian methods to efficiently search across all possible subsets of predictors in terms of effects (in our case, $\sum_{n=0}^{10}\binom{21}{n}$ subsets could exist); we call this the Selection Synergy Model. We find that both models fit the data significantly worse than our proposed model with no synergy (Proposed Model, marginal log-likelihood = −2,670; Full Synergy Model, marginal log-likelihood = −2,696; Selection Synergy Model, marginal log-likelihood = −2,714). This implies a Bayesian factor of 26 for the Full Synergy Model (compared to the Proposed Model) and a Bayesian factor of 44 for the Selection Synergy Model (compared to the Proposed Model). Both Bayesian factors are larger than six, implying that both synergy models fit the data significantly worse than the proposed model without synergies (Newton and Raftery 1994).[12] We conclude that, in the case of our data, synergies between POE media do not increase donation levels.

8. Conclusion

Blood banks improve people's lives with marketing. The challenging aspect of this marketing problem is driven by the perishability of blood, which prevents blood banks from simply over-collecting blood to continuously ensure that enough blood is stocked to meet demand. Thus, blood collections must remain close to certain target bounds. We investigate how marketing managers can use POE media to achieve this goal. Our results indicate that a successful POE media strategy for a blood bank goes beyond investing in paid media and capitalizing on owned and earned media.

Specifically, we first find that blood banks should follow inverse allocation rules for ad spending only in shortage and excess regions, but not in the cost-free region. In the cost-free region, the blood bank should increase spending even when blood donations increase to move the level of donations away from the shortage region on the fastest possible trajectory. Second, we find that an increase in the effectiveness of advertising instruments can lead to lower spending on these instruments and not more, as the extant literature suggests in for-profit settings. This result is driven primarily by the objective of the blood bank, which is not to maximize profit but to maintain donations within a target range. Third, we show that the value function (i.e., long-term performance) of the blood bank can decrease with owned and earned media activities, as the blood bank cannot adjust them with respect to donations, contrary to paid media. We illustrate the normative implications of the theoretical model using donation and POE media data from a community blood bank. This allows us to document that, consistent with Proposition 4, owned and earned media decreases the blood bank's value function about 37% of the time. Thus, POE media need to be carefully managed and can be critical marketing instruments in helping to optimize blood donations. Consequently, blood banks with limited advertising budgets can use inexpensive online paid media to efficiently manage blood donations. Moreover, this approach also applies to blood banks with larger operations, as neither the analytical results nor the estimation strategy makes any assumption about the size of the blood bank.

We propose two avenues for future research. First, in our study we distinguish between POE media based on their impact on the cost structure of the firm. There could however be other distinct characteristics of each media type. As more detailed data become available on how donors and customers interact with POE media (e.g., typical length of exposures, contributions to content, reactions to positive/negative/neutral content, etc.) a hierarchical set-up could be used to inform the estimates and to provide a better understanding of the inner workings of the underlying consumer processes. Finally, most of the empirical and strategic work in marketing academia is driven by managerial problems faced by for-profit firms. Yet, next to this sector exists an ever-growing sector of non-profit organizations. The U.S. nonprofit sector grew by 25% between 2001 and 2011, and contributes about 5.4% to the GDP (Roeger et al. 2012). The majority of non-profits are small, often local, organizations. According to the Urban Institute, of the one million public charities in the United States, about 75% reported less than $100,000 in annual gross receipts. The issues faced by these small local charities

[12] This result could also emerge due to the low levels of the daily media activity. We thank an anonymous reviewer for this intuition.

are very different from the typical for-profit setting, e.g., limited marketing budgets, constrained growth opportunities, strong dependency on outside funding, etc. However, despite their important roles in modern economies, very few marketing studies have focused on non-profits (e.g., Krishna and Rajan 2009, Arora and Henderson 2007, Ansari et al. 1996). We add to this literature by showing how state-of-the-art marketing science, especially novel online marketing methods, can be used by these small local non-profit organizations in their pursuit of charitable goals.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2014.0892.

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