Ehrenberg-Bass Institute **Working Paper**:

How sharing of supporters reveals competition amongst non-profit brands

This working paper, dated 19 March 2019, is forthcoming in the ***Journal of Marketing Management.***

Authors:

Margaret Faulkner - Ehrenberg-Bass Institute
Jenni Romaniuk - Ehrenberg-Bass Institute
Phil Stern - Ehrenberg-Bass Institute & University of Exeter

Accepted version for Journal of Marketing Management

Acceptance 5 June 2022

How sharing of supporters reveals competition amongst non-profit brands

Margaret Faulkner a*, Jenni Romaniuk a, Philip Stern b

a Ehrenberg-Bass Institute, UniSA Business, University of South Australia, Adelaide, Australia

b Ehrenberg-Bass Institute, UniSA Business, University of South Australia, Adelaide, Australia and Business School, University of Exeter, Exeter, United Kingdom

Margaret Faulkner

Ehrenberg-Bass Institute, UniSA Business, University of South Australia

61 North Terrace, Adelaide, South Australia 5000, Australia

Email: Margaret.faulkner@unisa.edu.au

Margaret Faulkner is a Senior Marketing Scientist at the Ehrenberg-Bass Institute for Marketing Science. Margaret's research interests include consumer behaviour, the effectiveness of marketing activities and brand management, particularly within the charity and not-for-profit context.

Jenni Romaniuk is a Research Professor at the Ehrenberg-Bass Institute for Marketing Science, based at the University of South Australia. Her research expertise spans brand measurement and management. She has authored two books on brand management published by Oxford University Press and is a past executive editor of the Journal of Advertising Research.

Philip Stern is Professor of Marketing at Exeter Business School and Visiting Professor at the Ehrenberg-Bass Institute. His research includes the prescribing behaviour of General Practitioners, innovative behaviour and gender's impact on brand loyalty.

How sharing of supporters reveals competition amongst non-profit brands

The traditional method of identifying non-profit competitors places those with similar objectives as forming the competitive set (looking inside out). This research provides a different perspective by looking at supporter behaviour and how this is shared across the non-profit sector (outside in). The research also applies the Duplication-of-Purchase law to a new context.

Four data sets from the US and Australia highlight that the overlap of supporters at cause-based groupings (e.g. children versus animal focused) and brand level (e.g. World Vision versus RSPCA) is largely determined by supporter numbers. This supporter-centric analytic view can highlight key competitors and potential collaborators that would be missed using the traditional inside-out perspective.

Keywords: competition; charity; Duplication-of-Purchase, non-profit, social marketing

Summary Statement of Contribution

Attracting supporters is an ongoing problem for the non-profit sector. We contribute new knowledge on the sector's market structure by showing how Duplication-of-Purchase patterns show how supporters distribute their support. This knowledge can identify key competitors and potential collaborators. We extend past research by including all forms of support, not just giving time or money. In addition, this research extends marketing science by showing how Duplication-of-Purchase applies to a new context.

Introduction

Commercial brand managers are very aware of other brands in the category and benefit from decades of empirical research to guide their marketing strategies, including tools to identify competitor overlap of customer bases (Goodhardt & Ehrenberg, 1969b); market segments

(Hammond et al., 1996); and likely outcomes of price changes (Dunn et al., 2020). Knowledge of other non-profits and charities, who compete for support, is also important for charities/non-profits as this underpins brand and sector performance. However, it is the mission not the marketing that drives people within charities and non-profits, and so it can be uncomfortable to treat another organisation with a similar mission as a 'competitor'. This may explain why there is a lack of broader, empirically based, academic and practical knowledge about how non-profit organisations compete for donor support.

As demand for charitable services increases, so does the need to garner support from any individuals who can donate money, goods or volunteer their time. Marketing strategies determine which supporters to target and avoid advertising wastage (Thornton, 2006). An essential requirement for setting strategies is a description of the market structure (Seaman et al., 2014). Even before the additional challenges posed by Covid-19 (Dempsey, 2020), there was a need for non-profits to understand the level and nature of competition in order to optimise the allocation of marketing resources (McLeod, 2020).

Charities face a perfect storm. The number of charities is growing with the USA recording a 19.5% increase from 2003 and 2013 (Giving USA Foundation, 2018) and Australia growing at 4% per annum as of February 2020 (Australian Charities and Not-for-Profits Commission, n.d.). At the same time, the proportion of people giving support has declined. In 2020, the decline shown since 2018 continued for Australia, with 61% having donated money and 30% volunteered in the four weeks prior to being surveyed (Charities Aid Foundation, 2021). In comparison, 69% donated money and 39% volunteered in 2017 (Charities Aid Foundation, 2018). The 2020 survey in Australia occurred prior to the first wave of Covid and following the major bushfires that led to an increase in support, with CAF noting this as one reason for its higher performance in 2020 compared to other western countries like the US (Charities Aid Foundation, 2021).

In the US, only 45% gave money and 25% volunteered in (Charities Aid Foundation, 2021), being a substantial decline from 2017 when 62% in the US gave money and 43% volunteered in the prior four-week period. Even without the effect of Covid, non-profits were facing increased competition for revenue streams (Hung & Wang, 2021),with attracting support in the face of increased competition being one of the key challenges facing non-profits (Giving Australia, 2016; Wallace et al., 2017). This results in higher fundraising costs and associated promotional expenditure which in turn can reduce the financial resources available to achieve non-profit missions (Castaneda et al., 2007; Cordes et al., 1999).

This paper makes three key contributions to knowledge: 1. It is to first uncover systematic patterns showing how charities and non-profits compete for support given by individuals. 2. It shows how this knowledge can help improve our understanding of supporters, as well as other charities and non-profits. A key aspect of designing any marketing strategy is a robust assessment of the market structure and brand competition (France & Ghose, 2016). Examination of market structure at both cause-based group and brand level addresses questions about market segmentation that can help formulate strategy (Easton, 1988; Porter, 1979), uncover submarkets (Urban et al., 1984) and influence product portfolios (Uggla, 2015). Market structure research to date has almost exclusively focused on for-profit categories, with the topic often ignored in the non-profit sector (Andreasen, 2006) or analysis providing mixed results that highlights the need for further research (Schmitz, 2021). The third contribution builds marketing theory by testing an existing model in a new context. A key objective of this paper is to test whether a model of brand competition (Duplication-of-

Purchase (Goodhardt & Ehrenberg, 1969a)), widely used in for-profit markets can be used in the charity sector to estimate charity cross-brand interaction. Extension to this context, will help non-profit marketers better understand the support environment and use this approach to guide competition or collaboration, thereby improving resource allocation. If the differentiated replication fails, then this demonstrates the discovery of a boundary condition for its use.

Understanding the competition

Alderson (1957) highlighted the importance of understanding competition and the benefits of seeking a differential advantage over competitors to set strategy (Hunt, 2017). Applying resource-advantage theory, Topalogu, et. al. (2018) propose that cost-effective delivery of superior social value can lead to a competitive advantage for non-profits. Charities face pressure and competition for their share of public funds, government grants and donors, volunteers and advocates, with competitive analysis helpful to show their relevance and performance (Saxton & Guild, 2010). However, to set strategies or to benchmark performance, the competitive set must first be identified.

Defining non-profit competition

This paper examines non-profit competition from the perspective of individual support, including provision of money, volunteering time, providing goods or any other form of support provided to charities/non-profit organisations. Ritchie & Weinberg (2000) propose three key forms of competition, based on potential for conflict versus opportunity to cooperate:

- Combative competition – where non-profits compete head-on to maximise their share of the market;

- Collegial competition – where non-profits work together and while not considering other organisations as ‘competitors’, will champion their unique contribution and focus on solving problems relevant to their mission and expertise;
- Alternative competition – where the pressures are more balanced and characterised by agreement of the problem but disagreement on the best solution.

Industry classification is a commonly used to identify competitors, and the International Classification of Nonprofit Organizations (ICNPO) is commonly used to classify causes, such as International Aid (Salamon & Anheier, 1996). These cause-based groups are used to define key competitors for support, such as Oxfam and World Vision competing for support because they focus on international aid, whereas WWF and RSPCA compete for support because of their animal welfare focus (Omura & Forster, 2014). Such classifications have informed research on competition in the sector, with Thornton, (2006) an example of where attention was restricted to charities that compete within relatively well-defined markets as indicated by national charity classification codes.

There is evidence that donors might split their support amongst non-profits that are dissimilar (Bennett, 2012). Therefore, World Vision’s competition for support might not be Oxfam, but be the WWF. This suggests the need for approaches that do not restrict competitor definition to the category of operation. This could lead to non-profit marketers identifying major competitors supporting other causes that may attract support away from the organisation and compromise the non-profit’s ability to fulfil its mission. Conversely, charities may discover opportunities for greater collaboration that can bring social and economic benefits with charities/non-profits that are not close competitors (Arenas et al., 2021).

The nature of non-profit competition

There are multiple reasons why the nature of competition may look different in the non-profit sector. Compared to for-profits, personal relationships and the emotional appeal of a charity's mission are more important to secure support (Bradach et al., 2008). Sargeant et. al. (2002). This explains how non-profits have markets for resource acquisition and resource allocation, but can also operate outside of market mechanisms to deliver support without profit and may not receive anything from the recipient in exchange for delivering their services. For example, when responding to disasters, non-profits provide relief as and when needed over offering goods and services at price and quality levels that optimise revenue (Sargeant et al., 2002).

For most non-profits, attracting and retaining supporters is secondary to the delivery of social goals (Ritchie & Weinberg, 2000). Organisational missions tend to relate to a well-defined area, e.g. social services or animal welfare. This mission driven approach forms distinct cause-based views of the market, which, coupled with the absence of donor-centric support data informs their view of the competition. The focus on marketing and monitoring competition is also likely to differ from for-profits. This is due to organisational structures where delivery of service (and needs of recipients) is separated from the marketing and fundraising operations (and needs of donors), leading to internal conflicts due to different goals and success parameters (MacKeith, 1994). Marketing strategy success is not evaluated on the quality or extent of services provided, but on the ability to generate support from potential donors (Saxton & Guild, 2010).

The notion of competition differs for each group, with demand for services often insatiable, thus making non-profits unwilling to consider other organisations as competitors (See Sargeant et al., 2002; Sharp, 2018). However despite an unwillingness to use the label, competition clearly exists within the market for supporters (Gayle et al., 2017).

An important aspect of the non-profit sector is the opportunity for collaboration, where non-profit organisations also benefit with help from other non-profits to achieve shared goals of advocacy and education (Lindenberg & Dobel, 1999). The tension of competing for supporters whilst also collaborating to achieve wider social impact also makes the sector distinct from for-profits (Mitchell & Clark, 2021). A recent example is when charities in the UK formed alliances to help vulnerable communities, such as people made homeless due to unemployment (Crick & Crick, 2020). However, pressure to compete can co-exist even within a collaborative framework. Larger charities can use brand communications to build awareness and try to 'own' an issue, even when acting collegially to address common problems (Saxton & Guild, 2010).

Relevance of for-profit theories of competition in the non-profit context

Theories of competition in the for-profit context are underpinned by the need to gain an advantage relative to competitors (Chetkovich & Frumkin, 2003; Hunt, 1995; Hunt, 1997; Hunt & Morgan, 1997). However non-profits focus on the delivery of social goals (Ritchie & Weinberg, 2000), so theories of competition developed in the for-profit context to achieve financial outcomes may have little relevance. The economic concept of the free-rider, (the tendency to let others pay for the costs of public goods that are available to all (Piliavin & Charng, 1990), also fails to translate over from for-profit to non-profit. To illustrate; the impact of a new and large funding body, such as the Bill and Melinda Gates Foundation, which provides support for global causes has not reduced individual support as predicted by the free-rider principle (Echazu & Nocetti, 2015). On the other hand, Resource-Advantage theory, where competition is perceived as an ongoing struggle among firms for resources that will translate into competitive market advantage and superior financial performance, is shown to translate across to the non-profit context (Topaloglu et al., 2018). Therefore, it is important to test for-profit theories of competition and approaches before applying them to non-profits in practice.

Measurement of (non-profit) brand competition

Examination of the structure of non-profit markets has historically focused on attitudes (Schlegelmilch & Tynan, 1989) or personal values (Wymer Jr, 1997). Analysing market structure from a supporter behaviour perspective is a neglected area of research. This research takes the opportunity to apply the Duplication of Purchase model, a generalised approach that analyses customer behaviour to uncover cause and brand level relationships, in the non-profit individual supporter context.

Duplication-of-Purchase Model

In for-profit situations, where consumer purchase data is widely available, the analysis of the cross purchasing of category buyers has revealed a law-like pattern describing how brands share buyers, referred to as Duplication of Purchase Analysis (e.g, Dawes, 2016; Ehrenberg et al., 2004a; Lees & Wright, 2013). Formally known as the "Duplication of Purchase Law" (DoP) (Ehrenberg et al., 2004a), where the level of duplicate buying between brands is quantified as the proportion of customers of one brand also found in the customer base of another. Dawes (2014) outlines the extensive empirical evidence that market structures reflect brand penetration (the number of buyers), rather than product attributes or brand positioning. DoP analysis of consumer markets shows that brands typically share customers in line with competitor brand penetration. This means that any brand shares a greater proportion of their customers with the biggest brand and fewer of their customers with the smaller brands in the market.

This competition model is a generalisation underpinned by the NBD-Dirichlet model (Goodhardt et al., 1984). The NBD-Dirichlet model can provide estimates for brand performance metrics such as brand penetration, loyalty and (via the Duplication of Purchase Law) competition. Its theoretical underpinnings are that each buyer has an underlying propensity to buy each brand in the category, which is stable for each buyer, but varies across buyers (Ehrenberg et al., 2004b). These propensities are revealed through examination of panel data to understand how brands share customers. The NBD-Dirichlet model, uses competitor brand penetration to predict competition, with every brand sharing more customers with large share brands and fewer customers with smaller share brands. If this generalisation is found to hold for charities and non-profits it would provide an alternative understanding of competition compared to the traditional classification/cause perspective. It could also highlight opportunities for charities and non-profits to engage in collaborations with other charities/non-profits with a similar mission.

The duplication of sharing pattern was first observed in audience behaviour and is known as the 'Duplication of Viewing Law' (DoV) (Ehrenberg & Goodhardt, 1969; Goodhardt, 1966), and later shown to apply to brand purchases in a variety of categories from tourism destinations, to car buying, to radio station listening (Dawes et al., 2009; Ehrenberg & Goodhardt, 1968; Lam & Ozorio, 2013; Lees & Wright, 2013; Lynn, 2013). An empirical test of the presence of DoP is a high correlation between the average sharing for brands and penetration levels (Faulkner et al., 2014).

As well as providing predictions for sharing across brands, DoP analysis identifies whether or not a market has partitions, i.e. a sub-set of brands which share consumers at levels higher than expected. Partitions are shown when observed sharing deviates from duplication estimates calculated from the combination of: a) their respective brand penetrations; and b) the overall level of purchase duplication shown for the market (Dawes, 2016).

Research shows that most brands share customers based on the penetration of their competitors and the approach also identifies market partitions, such as luxury cars (Ehrenberg et al., 2004a). Deviations due to functional similarities persist and align to product differences that split the market, e.g. caffeinated versus decaffeinated coffee (Anesbury et al., 2021). DoP analysis can identify which functional similarities affect consumer behaviour (Dawes, 2016), and as market structures are typically stable over time (Anesbury et al., 2021), it provides useful information to better understand the nature of competition when setting longer term marketing strategies.

New entrants seeking donations appear to influence competitive conduct in a similar way to new entrants in for-profit markets (Gayle et al., 2017). If the DoP law holds, marketers in charities/non-profits can use this model to estimate the likely impact of new entrants on support levels.

There are four possible outcomes from applying DoP analysis to non-profit situations:

1. The analysis of non-profits' supporter overlap may show the DoP law does not hold, which would suggest that the non-profit category needs its own competition model.

2. DoP holds at cause-based group level, and that non-profits compete based on donor penetration, but non-profit brands within groupings compete more closely than with other causes. This would suggest non-profit marketers should view functionally similar non-profits

as rivals for donor support, but could partner with functionally different non-profits to grow donor support.

3. DoP holds at both cause-based group and brand level, which provides the opportunity for non-profits to learn from the extensive body of research generated by the for-profit sector.

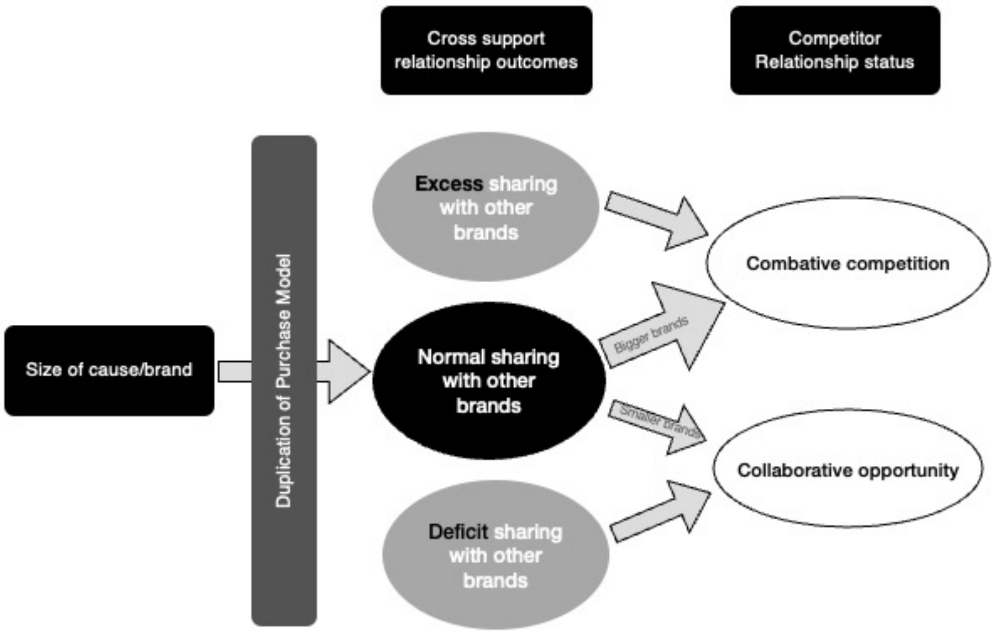
4. A hybrid model, whereby DoP holds overall, but apparently arbitrary partitions are revealed with an additional step required to explain such partitions. Such an outcome would lead to cause specific competition models and highlight which aspects of the non-profit environment (marketing or donors), are sufficiently influential to shape donor behaviour.

Hypothesis 1 (H1): Non-profit **cause**-based groups compete due on the size of their supporter base; the sharing of supporters between cause-based groups follows the DoP Law.

Hypothesis 2 (H2): Non-profit **brands** compete due on the size of their supporter base, with sharing of supporters between non-profit brands in line with DoP Law.

In addition to providing a new empirical framework to help understand non-profit marketing, this paper also makes a contribution by testing a potential boundary condition of the DoP empirical generalisation, and advancing wider academic knowledge (Uncles & Wright, 2004). The conceptual model tested in this research is depicted in Figure 1.

Figure 1: Duplication of support conceptual model testing level of combative competition based on size of competitive cause/brand



Research method

Unlike for-profit marketers, non-profits do not have regular access to panel data to capture the full range of individual support activity across different non-profits and support activities. Therefore, this research utilises survey data, as the only viable method to investigate the competitive market structure of non-profits. In all the studies used here, respondents were recruited via professional online panel providers, and were representative of the general adult donor population. The use of online data collection reduces the likelihood of social desirability bias, thereby offering a greater level of honesty in responses (de Leeuw, 2012).

Brand measurement follows the process used with for-profit brands (Ehrenberg et al., 2004b), with brand penetration (%) calculated as the number supporting the brand at least once, divided by the total number of potential supporters. To gain measures of duplication, cross-tabulation of penetration provides the number of shared supporters, dividing this number by the total number of supporters for each brand shows duplication as a % of brand supporters.

Table 1: Outline of constructs, variables and scale items captured for Duplication of Support analysis

Construct	Variable	Scale item
Cause/brand Penetration	Calculated variable at cause (brand) level: The number supporting the cause/brand at least once, divided by the total number of potential supporters	See below for items captured in data collection used to calculate cause/brand level metrics from binary calculated variable of whether support was provided in timeframe or not.
Cause/brand Duplication of Support	Calculated variable at cause/brand level: The number supporting each paired cause/brand combination at least once, divided by the total number of potential supporters for the cause/brand	See below for items captured in data collection used to calculate cause/brand level metrics from cross-tabulation of calculated variable of whether support was provided in timeframe or not.
Individual level cause (brand) Support	Calculated variable: Identified if individual respondent supported the cause/brand at least once in the timeframe captured looking across all support variables	Binary variable (1, yes supported, 0, not supported)
		Thinking about non-profit organisations in general, this can include sporting associations, community groups and environmental organisations, as well as charities, have you provided support in any of the following ways over the last 12 months? (Binary variable (1, yes supported , 0 not supported)
	Monetary Support	Donating cash
	Donation of Goods	Donating goods such as clothes, furniture
	Volunteering	Volunteering your time
	Buying products	Buying a product produced by a non-profit organisation
	Buying lottery/raffle tickets	Purchasing a lottery/raffle ticket
	Child/family sponsorship	Sponsorship of a child or family
	Animal sponsorship	Sponsorship of an animal
	Will bequest	Establishing a bequest in your will
	Pro-bono work	Pro-bono work in a specialist area
	Blood Donation	Donating blood
	Event participation (post 2011)	Participated in a charity event(s) (e.g. fun run, quiz night, fashion parade,

	Other (Please specify)	

Data description

Our scope covers data from the US and from Australia. In April 2011, 803 respondents from Atlanta, Georgia in the US completed the survey. Sample characteristics were as follows: 71% female, 13% 18-24, 28% 25-34, 21% 35-44, 22% 45-54 and 16% 55-64 years of age. 84% (n=672) indicated charity support in the previous 12 months. In the same month, 901 Australians were also surveyed, drawn from the cities of Sydney and Melbourne to broadly represent the population. Sample characteristics were as follows: 55% female, 7% 16-24, 15% 25-34, 17% 35-44, 19% 45-54,17% 55-64, and 25% over 65 years of age. 87% of respondents reported non-profit support in the prior year.

A further brand level data set from the US in 2016 replicated the study with 350 respondents self-reporting support in the previous six months. Respondents were drawn from across America to broadly represent the population, sample characteristics were as follows: 53% female, 18% 16-24, 23% 25-34, 23% 35-44, 17% 45-54 and 19% 55 to 64 years of age.

In all surveys, respondents were asked to think about non-profit organisations in general, as well as charities, before indicating the type of support they had given. The survey design assisted recall by prompting for the donations of money, goods, volunteering, buying products or any other support activity. Coding 'other' responses led to adding attending/ organising events for surveys post 2011. Aided-recall methods are helpful to capture easily forgotten behaviour, with recognition suggested to be superior to recall in prompting giving and volunteering behaviour (Cnaan et al., 2011).

Duplication of Support Analysis – Model estimations

The typical model estimations come from the Duplication Coefficient D, which is computed from the average of the observed duplications for all pairs of brands divided by their average percentage of supporters (also referred to as penetration) (Ehrenberg et al., 2004a). An underlying assumption of this model is that the relationship between average observed duplications and penetration is linear. As penetration approaches the 100% ceiling, the relationship reveals itself to be curvilinear, which renders the D coefficient unable to generate accurate estimates. Therefore, the data was checked to see if the D coefficient fits or if a different model is required. To examine how closely predicted data points are to observations, the Mean Absolute Error (MAE) is an appropriate measure, and is calculated by looking at the differences between the average duplication and the expected duplication (Lees & Wright, 2013).

Results

Non-profit cause-based group competitive market structure

To test the first hypothesis regarding cause-level market structure, cause-based groups were extracted from the US Charity Navigator website https://www.charitynavigator.org, and condensed into ten ICNPO groupings (Salamon & Anheier, 1996). Table 2 shows the observed data for cause-based groups in the US along with the average sharing estimates based on the best-fit linear model: $y=35*\ln(x)-67$, while Table 3 shows the cause-level deviations from average sharing scores for cause-based groups. The USA cause-level Pearson's correlation of average sharing scores with penetration is 0.95, $p<0.01$ and MAE between actual and predicted sharing is 3.2pp. These results are replicated in Australia with Pearson's correlation co-efficient 0.98, ($p<0.001$), between average sharing levels and the penetration and MAE is 2.1 (see Table 4 for deviations and Table A1 in the appendix for observed data).

Interpreting deviations

The first deviation of note is evidence of the Natural Monopoly Law (Dawes, 2020), in the USA, with the biggest cause-group (Social Services) sharing fewer of its supporters with other cause-groups. The reduced sharing occurs despite Social Services being the cause-group that has the highest over-lap with supporter bases of all other cause groups, highlighting that Social Services is monopolising supporters. This pattern is not as evident in Australia due to the lack of a dominant cause-type, with the most commonly supported cause, Social Services, only achieving 45% penetration (compared to 66% penetration in the USA).

The second deviation of note is a consistent negative deviation for religious charities in the USA, which share supporters -15 percentage points below the predicted average. This suggests that in the USA, every other cause-type competes less for support with religious non-profits. Therefore, it will be harder to attract supporters from these non-profits but also other cause-types are less likely to lose supporters to these non-profit types. This pattern was less evident in Australia, possibly due to the Australia being a less religious society with only 18% of Australians saying they pray daily compared to 55% of American adults (Fahmy, 2018).

As explained by Dawes (2016) partitions occur when at least two options have higher duplication than expected in both directions (from Option A also buying Option B and Option B also buying Option A). If non-profit brands compete more closely for supporters, the percentage of sharing between the brands will be higher than the Average Duplication reported between the partitioned brands, and sharing will be at lower levels with the other brands in the market. Visual inspection can identify partitions, as cells in a partition will be markedly different to the column average, or to other cells in the column (Nenycz-Thiel et al., 2009). For commercial brands a threshold of 20% above or below the estimated overlap in customers has highlighted managerially useful deviations (Tanusondjaja et al., 2016). In our results there are no deviations at that level. Reducing the threshold to >=+/-10 percentage points difference from average on both directions indicates two deviations in the USA; Philanthropic Intermediaries & Voluntarism Promotion with Development & Housing; and Development & Housing with Law, Advocacy & Politics. In Australia, Philanthropic Intermediaries & Voluntarism Promotion again shows a deviation, but this time it is under-sharing with International. The ability to identify deviations allows marketers to focus attention on areas where sharing is higher or lower than estimated by the DoP model, rather than needing time to investigate all results. As there are no obvious reasons for the deviations highlighted here, the threshold of 20% figure may be appropriate for this context as well.

The main finding for marketers is that DoP analysis confirmed the biggest competitor is Social Services. All causes share a greater proportion of their supporters with Social Services, and sharing with other causes is based on the size of the other cause, not on the similarity in mission. Therefore, support for H1 is found with sharing in line with the popularity of each cause-based group. The results suggest that DoP extends to the non-profit sector at cause level, as cause-based groups compete with other cause types based predominantly on the number of supporters they attract.

Table 2: Duplication of support to cause-based groups US 2011 (n=672)

	% of American supporters who also supported each cause									
Non-profit cause	Pen	SS	Rel.	E&R	Env.	Hea.	C&R	Intl.	P & V	D&V	LAP
Social Services	66		46	48	44	38	36	32	21	20	19
Religion	45	68		45	38	33	35	26	21	17	17
Educ & Res.	44	72	46		50	50	47	36	24	25	27
Environ.	39	74	43	55		44	50	37	24	24	29
Health	33	75	45	66	52		48	39	24	26	28
Cult. & Rec.	31	76	51	64	64	51		49	28	30	34
International	25	85	47	64	61	52	62		31	33	35
Philanth & Vol	17	80	54	60	54	45	51	44		38	29
Dev & Housing	16	83	48	68	60	53	60	50	41		40
Law, Adv/ Pol	16	78	48	75	73	58	68	54	32	41	
Average	33	77	48	61	55	47	51	41	27	28	29
Estimated Dup.		**75**	**63**	**62**	**57**	**52**	**50**	**42**	**30**	**27**	**27**
Difference		1	**-15**	-1	-2	-5	1	-1	-3	1	2
Model to generate estimates: y=35*ln(x)-67, MAE 3.2, Correlation between ave. Dup and penetration = 0.95, p<0.01											

Table 3: Deviations from DoP model to cause based groups US 2011 (n=672)

	Deviation from Column average: US supporters who also supported other causes									
US Non-profit sector	Soc. Serv	Relig	Ed & Res.	Envt	Health	Cult/ Rec.	Intl.	P & V	Dev/H ous.	Law, Adv/ Pol.
Social Services		-16	-14	-13	-14	-14	-10	-9	-7	-8
Religion	-8		-17	-19	-19	-15	-16	-9	-10	-10
Educat. & Res.	-3	-16		-7	-2	-3	-6	-6	-2	0
Environment	-2	-19	-6		-8	0	-4	-7	-3	2
Health	-1	-17	5	-5		-2	-3	-6	-1	1
Culture & Rec.	1	-12	2	6	-1		7	-2	3	7
International	10	-15	3	3	0	12		1	6	8
Philanth. & Vol.	5	-9	-2	-3	-7	1	2		**11**	2
Dev. & Housing	8	-15	7	3	1	10	9	**11**		**13**
Law, Adv/ Pol	3	-15	14	15	6	18	12	2	**14**	
Average Dup.	1	-15	-1	-2	-5	1	-1	-3	1	2

Table 4: Deviations from DoP model to cause based groups (n=782)

	Deviation: Australian supporters who also supported each cause									
Australian Non-profit sector	Soc. Serv	Ed & Res.	Health	P & V	Intl.	Cult/ Rec.	Envt	Relig.	Dev/ Hous.	Law, Adv/ Pol.
Social Services		-4	-1	-9	-3	-2	-7	-2	1	1
Educat. & Res.	-4		9	-1	0	3	-3	-5	2	1
Health	-2	10		0	-1	4	1	-6	1	2
Philanth. & Vol.	-12	-1	2		**-13**	3	-4	-8	2	1
International	-2	0	1	**-14**		-1	4	-1	6	6
Culture & Rec.	-3	3	5	2	-2		0	-7	2	1
Environment	-10	-5	3	-5	4	1		-8	1	4
Religion	-2	-11	-10	-12	-1	-9	-11		1	0
Dev. & Housing	2	4	1	2	10	3	1	0		4
Law, Adv/ Pol	8	7	17	6	31	7	20	-1	13	
Average Dup.	**50**	**52**	**45**	**35**	**40**	**35**	**34**	**21**	**22**	**8**
Estimated Dup.	52	50	42	37	36	34	34	25	20	8
Deviation	-1	2	3	-3	4	1	0	-4	3	1
Penetration	45	44	36	32	31	29	29	21	16	5
Model to generate estimates: y = 1.06(x)+8, MAE 2.1, Correlation = 0.98										

Brand level competitive market structure

To test the second hypothesis, supporters were asked to indicate which non-profit brands they had supported in the last 6 months (US) or 12 months (Australia). In both countries, only brands mentioned by more than 50 respondents are analysed to avoid relying on percentages with very low sample bases. This resulted in seven brands in the US and eleven brands in Australia (the difference is due to the longer time frame).

Table 5 provides the observed data for US supporters, with the deviations from the estimated models shown in Table 6 (USA) and Table 7 (Australia). The result of the analysis is that average sharing is highly correlated with brand penetration (Pearson's correlation co-efficient between brand penetration and average sharing 0.98 ($p<0.001$) in the US and 0.99 ($p<0.001$) in Australia. MAE is 0.9 for brand sharing of US supporters, with MAE is 1.3 for brand sharing of Australian supporters). Therefore, the DoP law holds for US and Australian data, with sharing of supporters declining for smaller brands.

Table 5: Duplication of support at brand level US 2016 (n=350)

	% of American supporters who also supported each brand							
Brand	Pen	GW	SA	St Jude's	ACS	ARC	F4P	United Way
Goodwill	60		57	38	28	28	23	20
Salvation Army	40	86		43	33	37	28	26
St Jude Children's Research Hospital	30	77	58		46	40	33	29
Am. Cancer Soc.	23	73	57	59		**54**	34	33
Am. Red Cross	21	80	69	56	**59**		35	28
United Way	18	77	65	56	45	42		34
Food for Poor	17	70	59	49	44	34	34	
Average Dup.		**77**	**61**	**50**	**43**	**39**	**31**	**28**
Estimated.		76	61	50	41	37	30	29
Abs. Error		2	0	0	2	2	1	0
Model to generate estimates = 37*Ln(X)-76; MAE 0.9, Correlation 0.998								

Table 6: Deviations from DoP model at brand level US 2016 (n=350)

	Deviation : US supporters who also supported each brand						
US Brand support	Goodwill	Salvation Army	St Judes Children's Hospital	American Cancer Society	American Red Cross	Food4 Poor	United Way
Goodwill		-4	-12	-15	-11	-8	-8
Salvation Army	9		-7	-10	-2	-3	-2
St Jude Children's Research Hospital	0	-3		3	1	2	1
Am. Cancer Society	-4	-4	9		**15**	3	5
Am. Red Cross	3	8	6	**16**		4	0
United Way	0	4	6	2	3		6
Food for Poor	-7	-2	-1	1	-5	3	
Average Dup.	77	61	50	43	39	31	28
Estimated Dup.	76	61	50	41	37	30	29
Difference	2	0	0	2	2	1	0
Penetration	60	40	30	23	21	18	17
Model to generate estimates = 37*Ln(X)-76; MAE 0.9, Correlation 0.998							

Table 7: Deviations from DoP model for Australian brands 2011-12 (n=481)

	Deviation: Australian supporters who also supported each brand									
Australia Brand support	Salv. Arm.	St V. d Pl.	Can. Cncl.	Red Cross	Nat. BCF	Smith Fam.	Guide Dogs	RSPCA	Leg -acy	RSL	Hrt. Fnd.
Salvation Army		-4	-4	-6	-6	-3	-7	2	-2	-1	
St Vin. de Paul	-1		6	2	-3	2	-3	-1	-1	-1	-1
Cancer Council	1	10		3	-4	3	1	-2	-2	0	1
Red Cross	-9	-1	-1		**-16**	2	-4	-4	-1	-1	-9
Nat. Breast C. F.	1	0	-2	**-11**		-2	4	3	3	4	1
Smith Family	0	3	2	5	-5		0	-3	-1	-1	0
Guide Dogs	-7	-5	0	-2	1	0		-4	-2	2	-7
RSPCA	1	-11	-13	-9	-4	-10	-11		-2	-2	1
Legacy	5	4	-2	5	7	2	1	4		2	5
RSL	11	7	14	9	28	6	20	3	10		11
Heart Found.		-4	-4	-6	-6	-3	-7	2	-2	-1	
Average Dup.	77	56	58	54	48	35	37	35	33	31	32
Estimated Dup.	78	57	56	53	46	37	36	33	33	32	31
Difference	-1	-1	2	1	2	-2	1	2	0	-1	1
Penetration	66	46	45	42	36	27	26	24	24	23	22
Model to generate Estimates = 1.1(x)+2, MAE 1.3, Correlation 0.99											

Explaining deviations

If there is evidence of cause-based partitions at brand level we would see non-profit brands with similar causes sharing more customers than expected. For instance, Salvation Army and Food For The Poor both deliver food to communities in the USA. In Australia, Cancer Council and National Breast Cancer Foundation both provide cancer support. In the USA there is only one deviation of note, higher than expected sharing between the American Cancer Society and the American National Red Cross, sharing supporters 15 and 16 percentage points higher than respective averages. In Australia, there is also only one deviation of note, under-sharing between Red Cross and National Breast Cancer Foundation. However, neither deviation comprise pairs of non-profits from the same cause, providing further evidence of the Duplication of Purchase Law holding. Therefore, hypothesis two is also supported and non-profit brands compete to a greater extent based on the level of support they attract than based on the cause-based group they operate within.

Discussion and Implications

The aim of this research is to see if a well-established empirical law on how brands compete for customer patronage holds in the charity and non-profit market. Our testing involved two countries (USA and Australia) and two levels of competition (cause and brand level). The results show that the Duplication of Purchase law extends to the non-profit context, aligning with the third possible outcome, i.e. DoP holds at both cause-based group and brand level, extending its application to the sector. At both levels of aggregation, the key determinant of competition for supporters is the number of supporters of the non-profit cause/brand, i.e. its market penetration. This informs our understanding of the drivers of brand equity and the advantage that comes with having a large current customer base.

While it is attractive to believe that it is possible to build a strong brand with a small, very loyal customer base, this does not appear to be supported by evidence (Ehrenberg, 1993). Customers of a small brand are also buying bigger brands, and a small non-profit supporter base is also supporting other bigger non-profits. Understanding this competition in memory gives a more realistic picture of the challenges that smaller non-profits face when trying to get more support from existing supporters.

The same pattern occurs when looking at the cause level, for example, in the US, 66% support Social Services, with all other causes sharing on average 77% of their supporters with Social Services irrespective of the cause-based group. This means any brand in any cause type, no matter how similar or different to Social Services, should expect around 4 in 5 of its supporters to also be supporting a Social Services charity/non-profit. Therefore, while the long-term aim might be to grow the total level of support (with competition viewed as collegial or an alternative form of competition as per Ritchie & Weinberg (2000)), in the short-term total only a limited pool of support is available and the Social Services cause provides the biggest competition for that pool (all causes are competing head-on with Social Services).

The two data sets allow us to see the Duplication of Purchase Law in action under different conditions. In Australia, two causes have similar Penetrations (Social Services at 45% and Education & Research at 44%), and they have similar average sharing levels (50% and 52% respectively), therefore both cause groups are similarly high competition for most other causes. Looking at competition at the brand level, shows the same pattern, i.e. the greatest sharing of supporters occurs with the biggest brand level in both the USA (Goodwill Penetration = 60%, Average sharing = 77%) and Australia (Salvation Army Penetration = 66%, Average sharing = 77%), regardless of the cause-based group brands operate within.

This challenges an underlying assumption of prior research that donors perceive non-profit brands as substitutes within a cause-based group (Gayle et al., 2017), and is contrary to prior research (e.g., Wymer Jr, 1997), which suggests that competition between charities is strongest within cause-based groupings and results in research designed to better understand differences to assist with creating targeted campaigns. With DoP analysis, if causes attracted different types of supporters, we would see excess sharing across similar cause-based groups and under sharing with the bigger brands operating in other areas. As this study allows for overlap of supporters across causes, it has shown that the strongest competitor is the one with the largest number of supporters, rather than another based on cause similarities. This supports prior research suggesting that support might be shared amongst non-profits that are dissimilar, and operating in separate cause-based groupings (Bennett, 2012).

Variations to the typical DoP pattern can provide information useful to better understand the competitive marketplace. A major deviation shown at the macro level, is that religious charities in the USA share fewer customers with other non-profit causes. Participation in religious/church activities is shown to increase the likelihood of volunteering and giving (Forbes & Zampelli, 2012; Jackson et al., 1995). Religious non-profits may benefit from the continued ability to engage directly with active members of their congregation, reducing the need to enter the market and compete directly with other non-profits. In addition to raising awareness of the need for support, suggesting concrete helping actions is within the power of members and said to assist in moving people through the helping process as per the Schwartz-Howard model (Jackson et al., 1995). That this deviation was not evident in Australia, which has weaker religious ties, shows the value of conducting this analysis in each market. An area of future research would be to conduct replications in more countries to look for consistency in deviations to understand the conditions under which they do or don't occur.

The results of this study build on existing marketing knowledge by extending the DoP to a highly differentiated marketing context, that of non-profit support. In addition to the scientific contribution of extending the DoP to a new context, the results have clear implications for practitioners.

This research highlights non-profits face a highly competitive market, which doesn't only include the non-profits that operate to support the same cause, but all other non-profits. Therefore, instead of focusing on non-profits with a similar mission as competition for support, non-profit brand managers need to widen their gaze to consider the wider charity/non-profit market. This opens the opportunity for smaller charities/non-profits to collaborate to give both a bigger voice either to compete against larger charities/non-profits or widen the pool of support available. This could increase the marketing efficiency of smaller non-profits.

The DoP is a useful tool for brand managers, whether seeking collaborative partners or looking to understand the nature of competition with other non-profits. By identifying deviations where excess sharing occurs compared to the average, close competitors can be identified and receive extra attention as any growth in support for a competitor with excess sharing is going to have a larger impact on the brand's level of support.

Non-profits may be more comfortable using DoP as a tool to help identify partners for collaboration opportunities (Sharp, 2018). Non-profits with lower than expected sharing with the target brand can be potential partners as there is less overlap in the supporter base and therefore opportunities to achieve cost savings due to scale efficiencies. For example, in the UK there are numerous charities focused on breast cancer. In 2018 two of these charities, Breakthrough Breast Cancer and Breast Cancer Care merged to form Breast Cancer Now (Breast Cancer Now, 2020). All charities in the UK will see effects, as Breast Cancer Now will have a higher sharing level with supporters from other charities, even those unrelated to breast cancer, due to higher penetration.

While being able to collect and analyse data in a specific market is the best option, the cost of collecting, analysing, and interpreting data may be out of reach or an unjustifiable cost for smaller non-profits. However, because the DoP law is such a well-established law, across a wide range of conditions, now that there is evidence that it holds in the charity/non-profit sector, marketers working in non-profits without access to data can still benefit from the fundamentals of the DoP and draw on the general implications to inform competition and collaboration strategies.

Limitations and future research

Although this research finds the same patterns in two very different geographic markets, to further generalise the findings it would be useful to extend the work to other countries and identify consistent deviations that could provide deeper understanding into the drivers of competitive market structure. Future research could also further explore competition between brands by increasing the sample size at brand level. Further exploration is also possible by looking at the different types of support provided (e.g., money versus time versus attending events) to see if supporters use of these activities also follows a Duplication of Purchase pattern. This would further inform the optimal selection of activities for non-profit marketers to offer as support mechanisms. It would also further deepen our understanding of broader supporter behaviour.

Acknowledgements

The authors would like to thank the anonymous reviewers whose constructive feedback has improved our manuscript.

References

Alderson, W. (1957). *Marketing Behaviour and Executive Action*. Richard D Irwin, Inc.
Andreasen, A. R. (2006). *Social Marketing in the 21st Century*. SAGE Publications
Anesbury, Z. W., Bennett, D., & Kennedy, R. (2021). How persistent are duplication of purchase partitions? *Journal of Consumer Behaviour*, *Ahead-of-print*(Ahead-of-print). https://doi.org/https://doi.org/10.1002/cb.1985
Arenas, D., Hai, S., & De Bernardi, C. (2021). Coopetition Among Social Enterprises: A Three-Level Dynamic Motivated by Social and Economic Goals. *Nonprofit and Voluntary Sector Quarterly*, *50*(1), 165-185. https://doi.org/https://doi.org/10.1177/0899764020948615
Australian Charities and Not-for-Profits Commission. (n.d.). *Are There Too Many Charities in Australia?* Australian Government. Retrieved 6 February from https://www.acnc.gov.au/for-public/understanding-charities/are-there-too-many-charities-australia
Bennett, R. (2012). What else should I support? An empirical study of multiple cause donation behavior. *Journal of Nonprofit & Public Sector Marketing*, *24*(1), 1-25.
Bradach, J. L., Tierney, T. J., & Stone, N. (2008). Delivering on the Promise of Nonprofits (pp. 1-18). Harvard Business Review.
Breast Cancer Now. (2020, n.d.). *Becoming Breast Cancer Now*. Breast Cancer Now. Retrieved 27 May from https://breastcancernow.org/about-us/becoming-breast-cancer-now
Castaneda, M. A., Garen, J., & Thornton, J. (2007). Competition, contractibility, and the market for donors to nonprofits. *The Journal of Law, Economics, & Organization*, *24*(1), 215-246. https://doi.org/10.1093/jleo/ewm036
Charities Aid Foundation. (2018). *CAF world giving index* (https://www.cafonline.org/docs/default-source/about-us-publications/caf_wgi2018_report_webnopw_2379a_261018.pdf?sfvrsn=c28e9140_4)
Charities Aid Foundation. (2021). *CAF World Giving Index 2021: A global pandemic special report* (https://www.cafonline.org/about-us/publications/2021-publications/caf-world-giving-index-2021)
Chetkovich, C., & Frumkin, P. (2003). Balancing margin and mission: Nonprofit competition in charitable versus fee-based programs. *Administration & Society*, *35*(5), 564-596. https://doi.org/10.1177
Cnaan, R. A., Jones, K. H., Dickin, A., & Salomon, M. (2011). Estimating giving and volunteering: New ways to measure the phenomena. *Nonprofit and Voluntary Sector Quarterly*, *40*(3), 497-525.
Cordes, J. J., Henig, J. R., Twombly, E. C., & Saunders, J. L. (1999). The effects of expanded donor choice in United Way campaigns on nonprofit human service providers in the Washington, DC, metropolitan area. *Nonprofit and Voluntary Sector Quarterly*, *28*(2), 127-151.

Crick, J. M., & Crick, D. (2020). Coopetition and COVID-19: Collaborative business-to-business marketing strategies in a pandemic crisis. *Industrial Marketing Management*, *88*, 206-213. https://doi.org/https://doi.org/10.1016/j.indmarman.2020.05.016
Dawes, J. (2014). Patterns in competitive structure among retail financial services brands. *European Journal of Marketing*, *48*(5-6), 7.
Dawes, J. (2016). Testing the robustness of brand partitions identified from purchase duplication analysis. *Journal of Marketing Management*, *32*(7), 695-715.
Dawes, J. (2020). The Natural Monopoly effect in brand purchasing: Do big brands really appeal to lighter category buyers? *Australasian Marketing Journal (AMJ)*, *28*(2), 90-99. https://doi.org/10.1016/j.ausmj.2020.01.006
Dawes, J., Romaniuk, J., & Mansfield, A. (2009). Generalized pattern in competition among tourism destinations. *International Journal of Culture, Tourism and Hospitality Research*, *3*(1), 33-53. http://www.ingentaconnect.com/content/mcb/ijcthr/2009/00000003/00000001/art00004
http://dx.doi.org/10.1108/17506180910940333
Dempsey, S. (2020, 14 May). *Charity giving forecast to fall 20-30 per cent*. Australian Institute of Company Directors. Retrieved September from http://aicd.companydirectors.com.au/resources/covid-19/charity-giving-forecast-to-fall-20-30-per-cent
Dunn, S., Dawes, J., & Bogomolova, S. (2020). The effects of competitive context on consumer response to price changes. *Journal of Marketing Management*, *36*(7-8), 608-632. https://doi.org/https://doi.org/10.1080/0267257X.2020.1720780
Easton, G. (1988). Competition and marketing strategy. *European Journal of Marketing*, *22*(2), 31-49. https://doi.org/ https://doi.org/10.1108/eb027337
Echazu, L., & Nocetti, D. (2015). Charitable giving: Altruism has no limits. *Journal of Public Economics*, *125*, 46-53.
Ehrenberg, A. (1993). If You're So Strong, Why Aren't You Bigger? *Admap*(October), 13-14.
Ehrenberg, A., & Goodhardt, G. (1968). Competitive rates of purchasing - Some inital results. *Admap*, *4*(April), 157-168.
Ehrenberg, A., & Goodhardt, G. (1969). Practical applications of the duplication of viewing law. *Journal of the Market Research Society*, *11*(1), 6-24.
Ehrenberg, A., Uncles, M. D., & Goodhardt, G. G. (2004a). Understanding brand performance measures: using dirichlet benchmarks. *Journal of Business Research*, *57*(12), 1307-1325.
Ehrenberg, A., Uncles, M. D., & Goodhardt, G. J. (2004b). Understanding brand performance measures: using dirichlet benchmarks. *Journal of Business Research*, *57*(12), 1307-1325. https://doi.org/10.1016/j.jbusres.2002.11.001
Fahmy, D. (2018). Americans are far more religious than adults in other wealthy nations. *Pew Research Center*. https://www.pewresearch.org/fact-tank/2018/07/31/americans-are-far-more-religious-than-adults-in-other-wealthy-nations/
Faulkner, M., Truong, O., & Romaniuk, J. (2014). Uncovering generalized patterns of brand competition in China. *Journal of Product & Brand Management*, *23*(7), 554-571.
Forbes, K. F., & Zampelli, E. M. (2012). Volunteerism: The Influences of Social, Religious, and Human Capital. *Nonprofit and Voluntary Sector Quarterly*, *43*(2), 227-253.
France, S. L., & Ghose, S. (2016). An analysis and visualization methodology for identifying and testing market structure. *Marketing Science*, *35*(1), 182-197.
Gayle, P. G., Harrison, T. D., & Thornton, J. (2017). Entry, donor market size, and competitive conduct among nonprofit firms. *International Journal of Industrial*

Organization, *50*, 294-318. https://doi.org/https://doi.org/10.1016/j.ijindorg.2016.10.003
Giving Australia. (2016). *Giving Australia 2016: Nonprofit Organisations Overview*. G. Australia
Giving USA Foundation. (2018). *Giving USA 2018: Highlights* (
Goodhardt, G. J. (1966). Constant in duplicated television viewing. *Nature*, *212*(5070), 1616.
Goodhardt, G. J., & Ehrenberg, A. (1969a). Duplication of viewing between and within channels. *Journal of Marketing Research*, *6*(2), 169-178.
Goodhardt, G. J., Ehrenberg, A., & Chatfield, C. (1984). The Dirichlet: A comprehensive model of buying behaviour. *Journal of the Royal Statistical Society*, *147*(5), 621-643. https://doi.org/10.2307/2981696
Goodhardt, G. J., & Ehrenberg, A. S. C. (1969b). Duplication of television viewing between and within channels. *Journal of Marketing Research*, *6*(2), 169-178. https://doi.org/10.2307/3149668
Hammond, K., Ehrenberg, A., & Goodhardt, G. J. (1996). Market segmentation for competitive brands. *European Journal of Marketing*, *30*(12), 39-49.
Hung, C., & Wang, L. (2021). Institutional Constraints, Market Competition, and Revenue Strategies: Evidence from Canadian Social Enterprises. *VOLUNTAS: International Journal of Voluntary and Nonprofit Organizations*, *32*(1), 165-177. https://doi.org/https://doi.org/10.1007/s11266-020-00300-y
Hunt, S. D. (1995). The resource-advantage theory of competition. Towards explaining productivity and economic growth. *Journal of Management Inquiry*, *4*(4), 317-332.
Hunt, S. D. (1997). Competing Through Relationships: Grounding Relationship Marketing in Resource-Advantage Theory. *Journal of Marketing Management*, *13*(No. 5, July), 431-445.
Hunt, S. D. (2017). Advancing marketing strategy in the marketing discipline and beyond: from promise, to neglect, to prominence, to fragment (to promise?). *Journal of Marketing Management*, 1-36. https://doi.org/10.1080/0267257X.2017.1326973
Hunt, S. D., & Morgan, R. M. (1997). Resource-Advantage Theory: A Snake Swallowing Its Tail or a General Theory of Competition. *Journal of Marketing*, *61*(October), 74-82.
Jackson, E. F., Bachmeier, M. D., Wood, J. R., & Craft, E. A. (1995). Volunteering and charitable giving: Do religious and associational ties promote helping behavior? *Nonprofit and Voluntary Sector Quarterly*, *24*(1), 59.
Lam, D., & Ozorio, B. (2013). Duplication of Purchase Law in the gaming entertainment industry—A transnational investigation. *International Journal of Hospitality Management*, *33*, 203-207.
Lees, G., & Wright, M. (2013). Does the duplication of viewing law apply to radio listening? *European Journal of Marketing*, *47*(3/4), 674-685.
Lindenberg, M., & Dobel, J. P. (1999). The challenges of globalization for northern international relief and development NGOs. *Nonprofit and Voluntary Sector Quarterly*, *28*(4), 4-24. http://journals.sagepub.com/doi/abs/10.1177/089976499773746401
Lynn, M. (2013). Lessons from Duplication of Purchase Data. *Cornell Hospitality Report*, *13*(3), 4-16.
MacKeith, J. (1994). Interdepartmental relations and voluntary organizations: An exploration of tensions and why they arise. *Nonprofit Management and Leadership*, *4*(4), 431-446. https://doi.org/https://doi.org/10.1002/nml.4130040406
McLeod, J. (2020). *Where to from here? The outlook for philanthropy during COVID-19* (

Mitchell, S.-L., & Clark, M. (2021). Rethinking non-profit brands through a volunteer lens: time for B2V. *Journal of Marketing Management*, *37*(5-6), 464-487. https://doi.org/https://doi.org/10.1080/0267257X.2020.1818804
Nenycz-Thiel, M., Sharp, B., Dawes, J., & Romaniuk, J. (2009). Competition for memory retrieval between private label and national brands. *Journal of Business Research*, *63*(1), 1142-1147.
Omura, T., & Forster, J. (2014). Competition for donations and the sustainability of not-for-profit organisations. *Humanomics*, *30*(3), 255-274. https://doi.org/10.1108/H-12-2012-0026
Piliavin, J. A., & Charng, H.-W. (1990). Altruism: A Review of Recent Theory and Research. *Annual Review of Sociology*, *16*, 27-65.
Porter, M. E. (1979). How Competitive Forces Shape Strategy. *Harvard Business Review*, *57*(March-April), 137-145.
Ritchie, R. J. B., & Weinberg, C. B. (2000). A typology of nonprofit competition: Insights for social marketers. *Social Marketing Quarterly*, *6*(3), 63-71. https://doi.org/http://dx.doi.org/10.1080/15245004.2000.9961122
Salamon, L. M., & Anheier, H. K. (1996). The International Classification of Nonprofit Organizations: INCPO-Revision 1, 1996 *Working Papers of the Johns Hopkins Comparative Nonprofit Sector Project* (pp. 24). The Johns Hopkins Insitute for Policy Studies.
Sargeant, A., Foreman, S., & Liao, M.-N. (2002). Operationalizing the marketing concept in the nonprofit sector. *Journal of Nonprofit & Public Sector Marketing*, *10*(2), 41-65. https://doi.org/http://dx.doi.org/10.1300/J054v10n02_03
Saxton, J., & Guild, M. (2010). *It's competition, but not as we know it* (https://nfpsynergy.net/its-competition-not-we-know-it
Schlegelmilch, B. B., & Tynan, A. C. (1989). The scope for market segmentation within the charity market: an empirical analysis. *Managerial and Decision Economics*, *10*(2), 127-134.
Schmitz, J. (2021). Is charitable giving a zero-sum game? The effect of competition between charities on giving behavior. *Management Science*, 1-19. https://doi.org/https://doi.org/10.1287/mnsc.2020.3809
Seaman, B. A., Wilsker, A. L., & Young, D. R. (2014, September 26). Measuring concentration and competition in the US nonprofit sector: Implications for research and public policy. (Ed.),^(Eds.).
Sharp, Z. (2018). Existential Angst and Identity Rethink: The Complexities of Competition for the Nonprofit. *Nonprofit and Voluntary Sector Quarterly*, *47*(4), 767-788. https://doi.org/i1.o0r.g1/107.171/0778/909897967460410818776600399
Tanusondjaja, A., Nenycz-Thiel, M., & Kennedy, R. (2016). Understanding shopper transaction data: how to identify cross- category purchasing patterns using the duplication coefficient. *International Journal of Market Research 58*(3), 1-12. https://doi.org/10.2501/IJMR-2016-026
Thornton, J. (2006). Nonprofit fund-raising in competitive donor markets. *Nonprofit and voluntary sector quarterly*, *35*(2), 204-224. https://doi.org/https://doi.org/10.1177/0899764005285951
Topaloglu, O., McDonald, R. E., & Hunt, S. D. (2018). The theoretical foundations of nonprofit competition: a resource-advantage theory approach. *Journal of Nonprofit & Public Sector Marketing*, 1-22. https://doi.org/DOI:10.1080/10495142.2018.1452818
Uggla, H. (2015). Aligning brand portfolio strategy with business strategy. *IUP Journal of Brand Management*, *12*(3), 1-7. https://search.proquest.com/docview/1728623618?pq-origsite=gscholar

Uncles, M. D., & Wright, M. (2004). Editorial: empirical generalisation in marketing [Editorial]. *Australasian Marketing Journal*, *12*(3), 5-12.
Urban, G., L, Johnson, P. L., & Hauser, J. R. (1984). Testing Competitive Market Structures. *Marketing Science*, *3*(2), 83-112.
Wallace, E., Buil, I., & de Chernatony, L. (2017). When does "liking" a charity lead to donation behaviour? Exploring conspicuous donation behaviour on social media platforms. *European Journal of Marketing*, *51*(11/12), 2002-2029. https://doi.org/https://doi.org/10.1108/EJM-03-2017-0210
Wymer Jr, W. W. (1997). Segmenting volunteers using values, self-esteem, empathy, and facilitation as determinant variables. *Journal of Nonprofit & Public Sector Marketing*, *5*(2), 3-28.

Appendix

Table A1: Duplication to cause-based groups Australia 2011 (n=782)

		% of Australian supporters who also supported each cause									
Non-profit cause	Pen	SS	E& R	Heal.	P&V	Intl.	Cult/ Rec.	Envt	Rel	Dev/ HouA	LAP
Social Services	45		48	41	29	34	32	27	23	20	7
Educat. & Res.	44	49		51	37	37	37	31	20	21	7
Health	36	51	62		38	36	38	35	19	20	8
Philanth. & Vol.	32	41	51	44		24	37	30	17	21	7
International	31	51	52	43	24		33	38	24	25	12
Culture & Rec.	29	50	55	47	40	35		34	18	21	7
Environment	29	43	47	45	33	41	35		17	20	10
Religion	21	51	41	32	26	36	25	23		20	6
Dev. & Housing	16	55	56	43	40	47	37	35	25		10
Law, Adv/ Pol	5	61	59	59	44	68	41	54	24	32	
Average		**50**	**52**	**45**	**35**	**40**	**35**	**34**	**21**	**22**	**8**
Pred. Dup.		52	50	42	37	36	34	34	25	20	8
Deviation		-1	2	3	-3	4	1	0	-4	3	1
Model to generate estimates: y = 1.06(x)+8, MAE 2.1, Correlation = 0.98											

Table A2: Duplication of support at brand level Australia 2011-12 (n=481)

	% of Australian supporters who also supported each brand											
Brand support		SA	St V. d Pl.	Can. Cncl.	Red Cross	Nat. BCF	SF.	GD	RSPCA	Leg .	RSL	Hrt. Fnd.
Salvation Army	66		52	51	48	43	32	32	29	27	28	27
St Vin. de Paul	46	75		49	47	42	36	35	31	32	31	27
Cancer Council	45	74	50		56	52	37	34	34	29	27	33
Red Cross	42	77	52	61		46	35	35	37	30	28	32
Nat. Breast C. F.	36	78	53	65	53		35	35	36	29	30	34
Smith Family	27	78	60	61	53	47		31	31	32	30	31
Guide Dogs	26	80	60	58	55	49	32		**47**	36	33	36
RSPCA	24	79	57	63	63	54	35	**51**		34	28	38
Legacy	24	74	59	53	52	44	36	40	34		**41**	32
RSL	23	78	61	52	50	47	35	38	30	**43**		32
Heart Found.	22	80	55	67	59	55	38	43	42	35	33	
Average Dup.		**77**	**56**	**58**	**54**	**48**	**35**	**37**	**35**	**33**	**31**	**32**
Pred. Dup.		78	57	56	53	46	37	36	33	33	32	31
Abs. Error		-1	-1	2	1	2	-2	2	2	-1	-1	1
Model to generate Estimates = 1.1(x)+2, MAE 1.3, Correlation 0.99												