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The Effect of The Net Promoter Score on Sales: A Study of a Retail Firm Using Customer and Store-Level Data

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Abstract

Existing industry-level evidence does not inform practitioners about when and by how much sales will grow as a result of an increase in NPS. We investigate the relationship between sales and NPS for a leading retail firm by combining individual stores' monthly sales data with data from customer satisfaction surveys from which we calculate NPS for every UK store in every month over a four-year period. We find nonlinear sales effects of (i) stores' own NPS and (ii) the average NPS of the other stores of the same company in the same region. Both NPS effects on stores' sales at first increase and then decrease over the five to 10 months after the product purchases to which the NPS refers. If every store could achieve a sustained increase in its NPS of one percentage point, then across all UK stores the additional annual sales would be around £3 million.

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1 Introduction

Some correlation between NPS and sales has been found in the literature at an industry level (Doorn et al., 2013; Keiningham et al., 2008; Keiningham et al., 2007; Reichheld, 2003). This encouraged the use of NPS by practitioners as the apparent positive association between NPS and sales is understandably appealing to managers. Consequently, two questions were asked by practitioners: "how do we drive the NPS so that we can grow our revenues?" and "if we manage to increase the NPS, when and by how much will our sales increase as a result?". The first question was addressed by Fiserova et al. (2017), the second question is investigated in this paper. This study uses the same corporate dataset as Fiserova et al. (2017) to investigate the timing and size of the expected effects of an increase in NPS on sales. This research project is, to our knowledge, the first one of its kind to have explored the relationship between sales and NPS within a firm having access to a large pool of customer-level retail data.

2 Literature review

A growing literature suggests that positive customer experience is essential for achieving customer satisfaction, word-of-mouth communications, loyalty, and competitive advantage (Jain et al., 2017). If we accept Berry's (2002) premise that customer experience can be managed, then we need to understand the customer journey and the points or stages where customer experience occurs and be able to measure the effectiveness of interactions at these key points.

Stages of the customer journey vary by the type of business, sector, and product or service. Those who deliver customer experience and change in organisations, i.e. the frontline management, understand their own business, products/services and customers and should therefore be able to identify the key points where interactions between the business and the customer occur. Indeed, when RBS used their understanding of their customer journey, they ended up with a system that had 'a more comprehensive diagnostic capability than that found in either academic or practitioner literature' (Maklan et al., 2017, p.111). Thus, it should be possible for academics to accept that managers are capable of using their knowledge and understanding of their customers to map their journey and define the key touch points to provide critical insight into their customer experience.

Nevertheless, even if the key stages of the customer journey are identified, the complexity of the customer experience and the consequent lack of clearly constructed definition makes it difficult to measure. Indeed, as Maklan et al. (2017, p.93) state, customer experience 'is defined so broadly – so "holistically" – as to exclude almost nothing; it has become the theory of everything'. However, to be able to measure the effectiveness of interactions between the business and its customers at each touch point requires a measure that is simple to use and communicate to a variety of stakeholders, ranging from frontline staff to company directors and shareholders.

Reichheld (2003) contributed to the debate on simplicity of measures by introducing his "Net Promoter Score" (NPS) which is derived from one question, namely: "How likely are you to recommend Company X to your friends and colleagues?" Reponses to this question are recorded on a scale from 0 to 10 and categorised into three groups: those who give a score of 0 to 6 are classified as *detractors*; 7 and 8 as *passive* customers; and 9 and 10 as *promoters*. The NPS is calculated by subtracting the proportion of detractors from the proportion of promoters.

The NPS has gained popularity in many industries not only because the measure is indeed simple to calculate, but it has face validity and intuitive appeal to managers and stakeholders and it is a comparable metric which companies can (and often do) include in their reports

(Brandt, 2007). However, perhaps the most important reason for the fast and widespread adoption and implementation of the metric across industries worldwide is Reichheld's (2003) claim that NPS can predict sales growth.

A number of studies have examined the potential of NPS to predict sales growth. Most studies, however, including the original one, have done so at an industry, i.e. macro level. Reichheld (2003) correlated average NPS scores with average sales growth rates of over 400 companies from a dozen industries. Other studies that attempted to examine the relationship between NPS and sales growth (Doorn et al., 2013; Keiningham et al., 2008; Keiningham et al., 2007; Morgan and Rego, 2006) used the same industry-level approach. Whether there is a relationship between NPS and sales at an industry level is, however, of little use to practitioners who ask questions like "when should we expect to see growth in sales when NPS increases?".

Managers and directors want to know when sales start growing as a result of an increase in NPS and the size of the effect that increase in NPS may have on the company sales. Only a large in-depth micro-level study can provide the answers. While Leisen Pollack and Alexandrov (2013) and Keiningham et al. (2008) moved the investigation of NPS from the macro to the micro level, their studies did not examine the relationship between NPS and sales growth (but rather focused on investigating whether NPS is a measure of loyalty). Clearly there is a need for a large longer-term micro-level study to investigate the relationship between the NPS and sales growth over time (Leisen Pollack and Alexandrov, 2013; Keiningham et al., 2008; Keiningham et al. 2007; Morgan and Rego, 2006).

In this study we address a number of shortcomings in the existing empirical literature. Researchers and practitioners are interested in (i) not only the macro (industry) level but also the micro (firm) level impact; and (ii) not only the qualitative nature of the relationship between NPS and sales – is there a relationship or not (as indicated by correlation coefficients) – but also in quantitative impact, i.e. the size of the effects (if any) and their timing. Furthermore, this study responds to the proposals of (iii) Keiningham et al. (2007; p44) for 'a longer-term, longitudinal study' to 'show that changes in satisfaction/loyalty metrics are important predictors of relative changes in revenue within firms'; and (iv) Morgan and Rego (2006; p437) for 'future research exploring interactions between customer feedback measures and examining possible nonlinear relationships with firms' business performance' to 'provide further insights for marketing theory'.

3 Context

DFS is the leading retailer of the UK living room furniture market with an 18.3% share (by value) of this £4.5 billion market in 2016 (DFS, 2018). DFS has a specialist focus on the retail upholstered furniture segment, which accounts for over two thirds of the living room furniture market driven by an approximately seven-year replacement cycle[1] (DFS, 2018). The strategy of DFS is to deliver, 'a world class customer experience' (DFS 2015, p61) and therefore they require a consistent framework to provide insight into the customer experience journey. To this end, DFS mapped the customer interactions with the company, defined key touch points, and implemented the Net Promoter System (Satmetrix, 2013). As a result, customer satisfaction surveys are emailed to customers at three distinct points over the first several months of product purchase.

[1] In this study, we can therefore rule out repeat purchases by the same customers as the reason for any potential effects of NPS on sales as the data were collected over a period of four years.

(i) The post-purchase (PP) survey is sent to customers who have purchased the product but not yet had it delivered. It contains the NPS question[2] and a set of questions enquiring about the customer satisfaction with the sales transaction. All products are made to order and thus the delivery of the product varies between two and 12 weeks from the point of purchase.

(ii) The post-delivery (PD) survey, also containing the NPS question and a set of questions enquiring about the customer satisfaction with the delivery transaction, is sent to customers who received their product within the previous week.

(iii) A final survey is sent to customers six months after their product purchase. Internal management information shows that customers who need to contact DFS about a transaction will do so within the first three weeks of purchase (in 98% of cases). Furthermore, approximately 80% of product faults will appear within 3 months of delivery. It is therefore reasonable to assume that most transactions and interactions between the company and its customers will have happened within 5 months of product purchase. As the final survey is intended for assessment of the overall relationship between the company and its established customers, rather than customer satisfaction with a particular transaction, it is sent six months after product purchase (as this point is considered to be sufficiently outside any individual transaction) and is referred to as the Established Customer (EC) Survey. In this study, we use responses to the NPS question recorded in this survey.

By the end of our sample period (July 2015), DFS had 105 stores throughout the UK, the Republic of Ireland (first store opened in 2012), the Netherlands (2014) and Spain (2015). In this study we use data from UK stores only (n=96) to ensure that we have an appropriate number of stores with sufficient time series depth to create a balanced dataset (see section 4 for further explanation). We use a large dataset of individual customer responses to the NPS question provided to us by DFS. We started with 386,695[3] customer satisfaction surveys generated by the 96 UK[4] stores in a period of four years (August 2011- July 2015). We were also provided with monthly sales data for every store during the same four-year period. However, although beginning with a very large dataset, we had to "funnel down" to a smaller dataset suitable to investigate the NPS effect on sales. We use the 44,585 responses to the Established Customer Survey to calculate the NPS for each store in each month: this is an aggregate measure derived by subtracting the proportion of detractors from the proportion of promoters of all the store's customers. Thus, we have a potential maximum of 4,608 observations (96 stores $\times$ 48 months). However, the following deductions took place to obtain our final sample for estimation: (i) DFS opened 30 new stores during the observation period, thereby reducing the number of stores with complete time-series coverage; (ii) NPS surveys were sent 6 months after the store opening, resulting in a further reduction in the number of NPS values available for matching with sales data; and, finally, (iii) the need for a balanced sample – i.e. the same number of monthly observations for each store – together with the use of lagging and leading values in our model further reduced the sample size resulting in 728 observations. Our empirical methodology is thus very "data-hungry" (Figure 1). This demonstrates that any company that may be interested in replicating this study using their own data must be prepared for 'patience', as serious time-series depth is required to generate the required balanced dataset.

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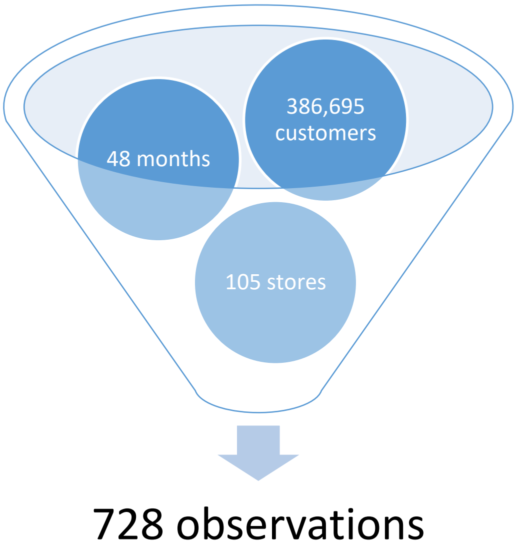
[2] How likely are you to recommend DFS to your friends, family and colleagues?

[3] Out of which 186,175 are from the PP surveys; 155,935 are from PD surveys; and 44,585 were ECs.

[4] DFS define 12 areas in the UK – these areas are used in this study to control for any effects that other DFS stores in close geographic proximity may have on a store's sales.

Figure 1. Data reduction



4 Estimation strategy

The estimated relationship between the NPS and stores' sales changes radically as we enrich our estimation strategy. We began with preliminary estimation strategies allowing only for an uncontrolled relationship at one point in time (the month in which the Established Customer Survey results are recorded) but progressed towards more developed strategies controlling for other potential influences on sales and allowing the influence of the NPS (if any) to unfold over a period of several months. For the moment, we do not interpret the quantitative meaning of the estimated NPS effects or comment on the statistical validity of the underlying models. We undertake these tasks for our preferred model. Here, we want only to establish that different estimation strategies yield inconsistent effects ranging from large and negative to large and positive:

- the simple correlation coefficient is -0.065 (the number of observations, n, is 3,864);
- the bivariate regression coefficient is -43,765 (n=3,864);
- the simplest possible static fixed-effects estimate – i.e. controlling for the time invariant effects of 101 stores – is -4,102 (n=3,864);
- static fixed-effects estimation controlling for time-specific effects of each month yields a coefficient of 1,724 (n=3,864);
- *static* fixed-effects estimation allowing for the NPS to affect sales from one to 12 months in the future are suggestive of positive effects on sales seven and eight months in the future as well as a quadratic pattern among the estimated coefficients such that the eighth-month effect is the largest with earlier effects being mainly smaller and later effects being all smaller (n=1,745, reflecting the loss of observations due to estimating with 12 lags of NPS); and, finally,
- *dynamic* fixed effects estimation allowing for the NPS to affect sales from one to 12 months in the future yields a coefficient of 8,496 on sales seven months in the future together with the previously hinted at quadratic pattern of influence, first rising with distance from sales but eventually falling towards zero (n=1,745).[5]

[5] These estimates are available in a Stata log file upon request.

Whereas simple modelling strategies lacking adequate controls may yield zero or even negative effects, successively enriched model specifications hint increasingly strongly at a positive connection between the NPS and sales. An additional inference from these preliminary estimates is that the benefits of greater quality and quality of estimates are achieved at the cost of substantial loss of observations (hence, degrees of freedom). Our empirical strategy begins with a novel methodology designed to exploit fully the information within a large corporate dataset.

We use panel analysis to exploit the variation of our data in two dimensions, i.e. across stores and over time. We reject static panel analysis on grounds of dynamic misspecification: in all our static models, a standard test reveals the presence of residual autocorrelation, which invalidates both point estimates and statistical inference. Accordingly, we favour dynamic fixed effects (FE) panel estimation – i.e. specifying our models with the first-lagged value of Sales, our dependent variable, among the independent variables – to account for otherwise unmodelled dynamics. This approach provides a solution to accommodating the joint occurrence of otherwise unobserved heterogeneity at the level of individual stores (fixed effects) and persistence in stores' sales over time (dynamics). However, two further issues remain to be addressed before we have a satisfactory approach to estimating the effect of NPS on sales.

Nickell (1981) identified the first problem. Fixed effects estimation yields biased and inconsistent estimates in dynamic panel datasets with "finite" time series depth, where finite includes the time series depth available to the present investigation (for each store we have a maximum of 48 monthly observations, although substantially fewer in many cases). To address this issue, we turn to the bias-corrected least-squares dummy variable (LSDV) estimator with bootstrapped standard errors designed for 'dynamic (possibly) unbalanced panel-data models with strictly exogenous regressors', which we implement by the Stata user-written programme *xtlsdvc* (Bruno, 2005, p473).[6]

The second problem to address is that even if the NPS has a positive effect on sales, theory does not offer guidance as to the precise timing of measurable sales effects. Accordingly, our starting point was some ad hoc reasoning informed by practitioner, hence product-specific, insight. First, it may take time for customers to form a settled opinion about their purchase and it will certainly take time (i) for existing customers to pass on these opinions and corresponding recommendations – whether positive or negative – in the normal course of social intercourse and (ii) for the subsequent influence of these opinions and recommendations on the search and purchasing decisions of family, friends and colleagues. Hence, the diffusion process is unlikely to begin immediately post purchase (in the same or in the following month) but is likely to take place subsequently over a period of several months. Second, experience of the product might lend authority to an existing customer's recommendations. If so, then recommendations become increasingly persuasive over time and thus an increasingly effective influence on sales. Third, however, the number of recommendations per existing customer per period will eventually decline as (i) the purchase loses novelty and becomes less of a talking point and (ii) as each additional recommendation reduces the remaining number of potential recommendations within a given social network.[7] Accordingly, we conjecture a period of at most 12 months over which the NPS can influence sales of the product under consideration. These three considerations have two implications for our model specification: we allow for the

[6] LSDV estimation is alternative nomenclature for FE estimation.

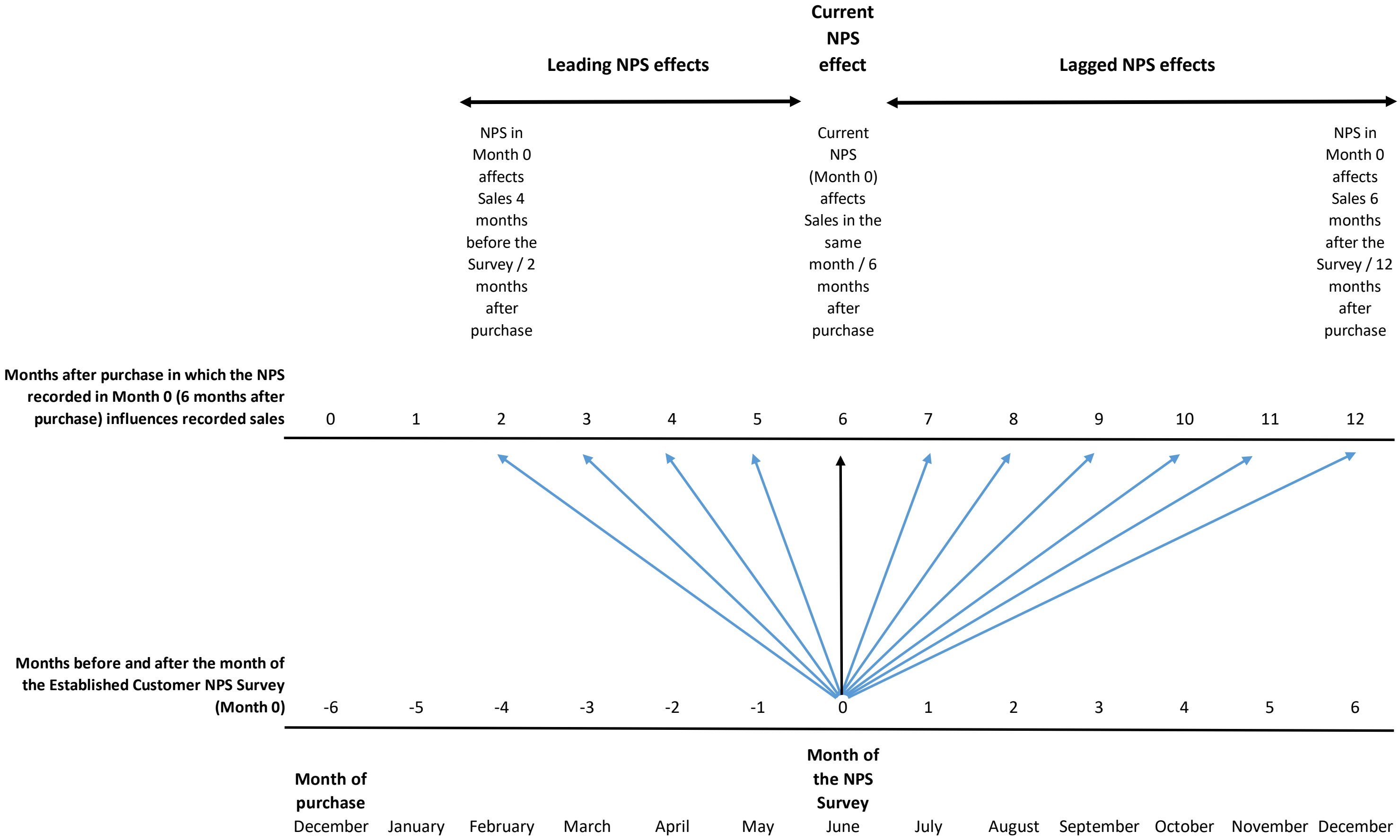
[7] We assume that only direct recommendations from the purchaser have an effect on sales.

impact of the NPS and associated customer recommendations on sales (if any) to take place from the second to 12 months after purchase; and we allow for the possibility that the pattern of the sales effects over time might not be a linear decline in strength (reflecting only our third consideration) but quadratic (gaining in strength according to our second consideration before eventually declining according to the third).

The NPS is derived from a survey completed in the sixth month after purchase. To allow for recommendations to influence sales from the second month to 12 months after purchase, we allow for the NPS to reflect judgements that may have already informed recommendations in *earlier* months as well as having the potential to inform recommendations in *later* months. Accordingly, we model the effect on current monthly sales of the NPS in each of the four months before the survey, in the month of the survey, and in each of the six months after the survey. Figure 2 provides a graphical depiction of the potential NPS effects on sales that we investigate. The top scale refers to months in which sales are recorded: in Month 0 the purchases occur to which the Established Customer Survey refers (and, hence, the derived NPS); future sales occur in Months 1-12 and will be subject of future monthly Established Customer Surveys, each one of which is hypothesised to give rise to the pattern of effects over time illustrated in Figure 2. The bottom scale depicts months relative to the Month of the Survey (0), from six months before (-6) to six months after (6). In our empirical analysis, we investigate the effects of the NPS in each month on sales

- in the same month as the Survey ("Current NPS effect"),
- up to four months before the Survey (-4 on the bottom scale) or two months after purchase (2 on the top scale) ("Leading NPS effects"), and
- up to six months after the Survey (6 on the bottom scale) or 12 months after purchase ("Lagged NPS effects").

Figure 2. NPS effects on sales over time (from 4 months before to 6 months after the Established Customer Survey – i.e. from 2 to 12 months post purchase)



Although we estimate a panel model, our empirical methodology integrates two strands of time-series econometrics.

1. We allow for the possibility that the sales effect (if any) occurs not only – or necessarily – in the month of the Established Customer Survey but also in months before and/or in months after. Hence, our model will include multiple monthly values of the NPS, comprising not only the NPS in the month of the survey but also the NPS in previous months ("leading" values) and/or the NPS in later months ("lagged" values). However, it is unwise to estimate models including many "lead" and/or "lag" values of one or more independent variables, because estimated effects are greatly impaired by multicollinearity (Almon 1965: 179; Gujarati 1988: 512). The solution introduced by Almon (1965) was to reduce multiple values – leads and/or lags – of an independent variable to polynomial functions. For example, to allow for a quadratic effect – whereby, say, the first monthly NPS value could have a smaller influence than the second and third but, thereafter, the influence of successive values declines – Almon's approach is to reduce large numbers of leading and/or lagged values to three variables (i.e. polynomial functions) denoted *Z*0, *Z*1, and *Z*2. Accordingly, we apply Almon's approach: we use all 12 leading, current and lagged values of the NPS to calculate these

three Almon functions.[8] Finally, we use the estimated effects of $Z0$, $Z1$, and $Z2$ in post-estimation calculations to recover each individual month's NPS effect.[9]

2. Appealing to well-established principles in time-series econometrics (Spanos 1986: Chapters 23 and 24 – in particular, pp.601-2; Hendry 1995: 339), the estimated coefficient on the lagged dependent variable in the dynamic models estimated below ($\hat{\lambda}$) measures the persistence of sales. Accordingly, 1-$\hat{\lambda}$ measures the rate of adjustment of current sales to changes in sales in the previous month, and 1/(1-$\hat{\lambda}$) can be interpreted as a persistence factor by which the estimated effects of $Z0_t$, $Z1_t$ *and* $Z2_t$ can be multiplied to obtain their long-run effects. In turn, we apply this multiplier to each individual month's recovered NPS effect (see Point 1 above) to obtain each individual month's NPS *long-run* effect. Each one of these long-run coefficients predicts the likely total eventual change in sales consequent upon a sustained change in the level of the NPS. These total or long-run sales effects reflect both (i) direct short-run effects and (ii) indirect induced effects. The direct short-run sales effects of NPS changes vary by month according to a quadratic pattern; i.e. first building to a maximum and then declining towards zero. Additional indirect induced effects of each month's effect occur via the estimated persistence coefficient.

In adopting the Almon approach to modelling distributed lags, we have to take into account that we are estimating a panel model and that our data has missing values. This is a potential problem, because if we create our Z variables from data with missing values then they could be defined in different ways across our observations. For example, consider two stores: Store 1 with complete NPS data (i.e. one value for each month); and Store 2 with just a single missing value (say, for month 47). In this case, for Store 1, in Month 48, $Z0_t$ is calculated (correctly) as $Z0_t = X_t + X_{t-1} + X_{t-2} + \cdots + X_{t-10}$; whereas for Store 2, $Z0_t$ is calculated (incorrectly) as $Z0_t = X_t + X_{t-2} \ldots + X_{t-10}$ (i.e. without X_{t-1}). Accordingly, we have to create a "balanced" dataset (i.e. one in which each store has a complete set of sales and NPS values for the same set of months). This provides another example of how methodological validity is very demanding of data.

Accordingly, our final modelling strategy is to analyse the effect – if any – of the NPS on sales by estimating a hybrid dynamic panel model with Almon distributed lags by means of applying bias-corrected LSDV estimation to balanced store-level datasets.

[8] We calculate these functions as follows:

$$Z0_t = \sum_{i=0}^{10} X_{t-i} = X_t + X_{t-1} + X_{t-2} + X_{t-3} + X_{t-4} + \cdots + X_{t-10}$$

$$Z1_t = \sum_{i=0}^{10} iX_{t-i} = 0X_t + 1X_{t-1} + 2X_{t-2} + 3X_{t-3} + 4X_{t-4} + \cdots + 10X_{t-10}$$

$$Z2_t = \sum_{i=0}^{10} i^2X_{t-i} = 0X_t + 1X_{t-1} + 4X_{t-2} + 9X_{t-3} + 16X_{t-4} + \cdots + 100X_{t-10}$$

where X denotes NPS and i denotes the order of the lag relative to Month 2 after purchase (t=0) – i.e. i= 0, 1, …, 10. Each of the $Z0$ parameters on X_t, … X_{t-10} is unity (one); the $Z1$ parameters = i (=0, 1, 2,…,10); and the $Z2$ parameters = i^2 (=0, 1, 4,…,100).

[9] Following Almon (1965) and the particularly clear account in Gujarati (1988: 534-40). We cannot outline the post-estimation derivation of the individual NPS effects within the word limit of this conference paper. A full technical explanation of our procedure is available upon request.

Our sales model is specified with the following explanatory variables.

- *$Sales_{t-1}$*.
  Static models uniformly displayed evidence of serially correlated residuals (ε_t). Hence, the requirement to specify a dynamic model. The first lag of the dependent variable (*t-1*) proved to be statistically significant at the five per cent level but the second did not.
- *$Z0_t$, $Z1_t$ and $Z2_t$*.
  The NPS is derived from customer responses to a survey completed six months after purchase. We allow for the possibility that the Established Customer Survey reflects established views that might have already informed recommendations in previous months. Accordingly, we allow for the NPS to affect current sales up to four months *before* completion of the survey – i.e. two months post purchase. We also allow time for existing customers to form firm judgements about the product and for the diffusion of these judgements as recommendations. Because we were unable to find evidence of systematic NPS effects beyond six months, we allow for lagged effects of the NPS for each of the six months after the Established Customer Survey – i.e. up to 12 months post purchase. We therefore investigate the presence (if any) of NPS effects on sales, month by month over a period of 11 months. We transform the current value, four leading values and six monthly lagged values of the NPS into three Almon functions, $Z0_t$, $Z1_t$ and $Z2_t$, thereby allowing the 11 monthly effects (if any) to display a quadratic pattern.
- *Z0_net area mean*, *Z1_net area mean* and *Z2_net area mean*.
  Each store belongs to one of 12 company-defined areas in the UK. We controlled for net area monthly average NPS – i.e. area monthly averages net of the store for which the mean NPS is calculated (to avoid double counting). This controls for the effects on a store's sales of the NPS of stores in close geographic proximity. For the reasons outlined for the stores' own NPS, we also include the current value, four leading values and six monthly lagged values of the monthly net area averages. We also transformed these into three Almon *Z* variables.
- *Store_DV*.
  Store fixed effects – i.e. a dummy variable for each store – control for all time invariant or "slowly-moving" characteristics of the store; for example, location-specific effects such as the area, the socio-demographic composition of the local population, influences from the regional/sub-regional economy, and so on. Because there is a complete set of store fixed effects, the model has no overall constant term.
- *Month_DV*.
  Monthly dummy variables control for all systematic influences that affect all stores more or less equally, including seasonal effects and advertising campaigns (which, in the case of our firm, are conducted nationally). Given that our sample is restricted to UK stores, this applies to all influences from the macroeconomic environment. In particular, the period dummies control for the effects of inflation. Our initial inclination was to deflate sales according to monthly changes in the price level. However, we were persuaded otherwise by two main considerations: (i) the lack of a deflator sufficiently precisely defined to apply to our particular firm; and (ii) advice from a senior board member that company prices were not influenced by inflation during our sample period, as the then moderate rates of inflation were of much less concern to the company than the desirability of maintaining its price points. For these reasons, we control for the potential effects of inflation alongside (and indistinguishable from) other systematic period influences. In addition, the inclusion of a full set of monthly dummies (excluding

the first as the omitted category) is the most flexible way to control for unobserved and thus unmodelled trend effects, should there be any.[10]

Accordingly, our full panel model to estimate the effects of the NPS on sales is set out in Eq.1:

$$
\begin{aligned}
&Sales_{s,t} \\
&= \hat{\lambda}_1 Sales_{s,t-1} + \hat{\gamma}_0 Z0_{s,t} + \hat{\gamma}_1 Z1_{s,t} + \hat{\gamma}_2 Z2_{s,t} \\
&+ \hat{\phi}_0 Z0\_net\ area\ mean_{s,t} + \hat{\phi}_1 Z1\_net\ area\ mean_{s,t} + \hat{\phi}_2 Z2\_net\ area\ mean_{s,t} \\
&+ \sum \widehat{Store\_DV}_s + \sum \widehat{Month\_DV}_t + \varepsilon_{s,t} \qquad \text{(Eq. 1)}
\end{aligned}
$$

where *s* indexes the individual stores, and *t* the months included in the balanced dataset. The effects to be estimated are the coefficients and dummy variables accented by ^. From Eq. 1, we derive: 11 coefficients estimating the long-run sales effects of the four lead values, the current value and the six lag values of the NPS (β_0^{LR} ... β_{10}^{LR}); and 11 coefficients estimating the long-run sales effects of the four lead values, the current value and the six lag values of the Net Area Mean NPS (β_{11}^{LR} ... β_{21}^{LR}).

[10] A variety of first-generation (assuming cross-section independence) and second-generation (allowing cross-section dependence) panel unit root tests conducted over different lag lengths (up to 12) and with and without deterministic time trends rejected the unit root null (i.e. non-stationarity) for our variables of interest, sales and NPS. Indications of deterministic drift terms support specification with monthly dummies to control for potential deterministic trend effects.

5 Results and discussion

The model set out in Eq.1 was estimated on a balanced dataset of 28 stores each with 26 monthly observations used in estimation (i.e. after accounting for the loss of observations due to estimating with leading and lagged values of the independent variables of interest and the first lag of the dependent variable). Appendix 1 provides descriptive statistics for the estimation sample.[11] The results are reported in Table 1a, which is followed by the derived estimates of the long-run effects of each variable of interest reported in Table 1b. (Store and monthly dummies have a control function and so are not reported or discussed.)

Table 1a. Bias-corrected LSDVC dynamic regression (bootstrapped SEs)

Dependent variable: Sales

Bias correction up to order O(1/NT^2)

	Coefficient	z-statistic *	P>z (p-value)
Lag1_SALES	0.17	4.42	0.000
Z0_10_NPSEC_bal	-7716	-0.99	0.322
Z1_10_NPSEC_bal	7174	2.26	0.024
Z2_10_NPSEC_bal	-698	-2.34	0.019
Z0_10_NPSEC_Mean_bal	-32164	-1.53	0.126
Z1_10_NPSEC_Mean_bal	19579	2.20	0.028
Z2_10_NPSEC_Mean_bal	-1512	-1.84	0.066

25 monthly dummy variables (March 2013-March 2015);
February 2013 is the omitted – baseline - category
28 Store fixed effects
* Computed from bootstrapped cluster-robust standard errors (clustered on store) (2,000 replications – there are no noteworthy differences from the SEs computed using either 400 or 100 replications)

The estimated coefficient on lagged sales is in the valid range of $0 < \hat{\lambda} < 1$ and gives a persistence factor (1/[1-$\hat{\lambda}$]) of 1.2048, suggesting that the long-run effects will be only a little larger than the short-run effects.[12] Hence, the long-run effect is arrived at very quickly, within two to three months. If a sales increase of £1 took place in the previous month then – other factors held constant – current sales (*t*=0) would increase by £0.17; in the next month (*t*=1), the induced sales effect would be £0.17× 0.17 = £0.0289; in the month after that (*t*=2), £0.17× 0.17 × 0.17 =£0.0049; … and so on. By the third month (*t*=3), the cumulative induced sales effect is 0.2046, only slightly less than the full multiplier of 0.2048, which in formal mathematical terms is reached after an infinite number of periods. This suggests that the long-run effects occur sufficiently quickly to be of practical rather than purely mathematical significance.

[11] Comparison of average monthly sales in the balanced sample with average monthly sales in the full and highly unbalanced sample reveals a difference of 12 per cent.

[12] The condition $0 < \hat{\lambda} < 1$ precludes both a random walk and explosive growth in sales, and ensures that the long-run NPS effect on sales is larger than the short-run NPS effect on sales.

Table 1b. Derived long-run effects of the Established Customer NPS on Sales

Month relative to purchase	Month relative to Established Customer Survey in Month 0	Coefficient derived from estimating Eq.1				Month relative to purchase	Month relative to Established Customer Survey in Month 0	Coefficient derived from estimating Eq.1			
Stores' own NPS						**Area net average NPS**					
			Estimated Coefficient	z-statistic	p-value				Estimated Coefficient	z-statistic	p-value
+1						+1					
+2	+4	β_0^{LR}	-9260	-0.99	0.322	+2	+4	β_{11}^{LR}	-38601	-1.53	0.126
+3	+3	β_1^{LR}	-1488	-0.22	0.823	+3	+3	β_{12}^{LR}	-16918	-0.94	0.347
+4	+2	β_2^{LR}	4608	0.91	0.363	+4	+2	β_{13}^{LR}	1134	0.08	0.936
+5	+1	β_3^{LR}	9029	2.00	0.046	+5	+1	β_{14}^{LR}	15557	1.19	0.235
+6	0	β_4^{LR}	11773	2.60	0.009	+6	0	β_{15}^{LR}	26349	1.95	0.051
+7	-1	β_5^{LR}	12842	2.82	0.005	+7	-1	β_{16}^{LR}	33510	2.43	0.015
+8	-2	β_6^{LR}	12235	2.80	0.005	+8	-2	β_{17}^{LR}	37042	2.76	0.006
+9	-3	β_7^{LR}	9952	2.42	0.016	+9	-3	β_{18}^{LR}	36943	2.95	0.003
+10	-4	β_8^{LR}	5993	1.40	0.162	+10	-4	β_{19}^{LR}	33214	2.69	0.007
+11	-5	β_9^{LR}	358	0.06	0.948	+11	-5	β_{20}^{LR}	25855	1.75	0.081
+12	-6	β_{10}^{LR}	-6953	-0.87	0.386	+12	-6	β_{21}^{LR}	14866	0.71	0.476

Table 1b reports statistically significant estimates suggesting that a store's NPS has a positive and economically meaningful effect on the store's sales over a five-month period (from five to nine months after purchase). This effect begins one month prior to the survey, increases during the month of the survey and again during the following month, and then fades during the second and third months after the survey. Figure 3 shows the sales effects for an average store in each month – from two to 12 months after purchase – in pounds (£) per month resulting from a sustained unit increase in (i) the stores' own NPS and (ii) the Area net mean NPS. Because NPS is measured on a scale bounded by ±1 (where 1 is 100% promoters and -1 is 100% detractors), a unit increase is an increase of the NPS from e.g. 0 to 1, i.e. 0 to 100%. However, econometrically estimated effects measure marginal, i.e. small changes. Moreover, for most businesses, feasible increases in NPS are likely to be small. Accordingly, on grounds of both econometric validity and business practicality, we interpret the effects of an increase in the NPS of 0.01 (i.e. an increase of 1 percentage point). Hence, for each of the long-run effects reported in Table 1b, the corresponding effect on sales in pounds sterling (£) is given by multiplying the estimated coefficient by 0.01.

In round terms, a *sustained* one percentage point improvement in NPS delivers – on average and holding other influences constant – an increase in sales of £90 (i.e. 0.01 × β_3^{LR}) plus a further £118 (i.e. 0.01 × β_4^{LR}), £128, £122 and £100, respectively, over the five-month period. Both before and immediately after this period, the effects are small and are not estimated with sufficient precision to warrant inclusion in the calculation. Nonetheless, a total increase in sales of £558[13] in every subsequent month – so long as the initial increase in NPS is sustained – represents an economically substantial effect from a small increase in NPS. If a similar increase were to be achieved by all 96 of the firm's UK stores and sustained for a year, then the annual increase in sales would amount to £643,000 (rounded).[14]

Also noteworthy is the effect on an individual store of the average NPS of the other stores in its area. Here, a one percentage point improvement, *ceteris paribus*, gives rise to statistically significant effects in the current period and in the next five months: respectively, in round terms, £263 (i.e. 0.01 × β_{15}^{LR}), £335 (i.e. 0.01 × β_{16}^{LR}), £370, £369, £332, and £259, likewise observing a quadratic pattern. Although the assumed increase in net area average NPS is small, if it were to be sustained then the total impact on the remaining store would be large: increased sales of £1,929 per month. Projected across 96 stores for a year this amounts to an annual sales increase of £2,220,000 (rounded). Therefore, if every store could achieve a sustained increase in its NPS of one percentage point then across 96 stores the additional annual sales over the long run would be in the region of £3 million.[15]

Figure 3 displays graphically the quadratic effects of both the store's own NPS (left-hand panel) and the area mean NPS (right-hand panel), which unfold over time, at first strengthening and then declining. Each dot depicts the respective "Estimated Coefficient" reported in Table 1b, while the vertical bars depict the associated confidence intervals (such that the shorter the bar the more precise the estimate; and estimates with bars overlapping the zero reference line indicate an estimate that cannot be statistically distinguished from zero).[16]

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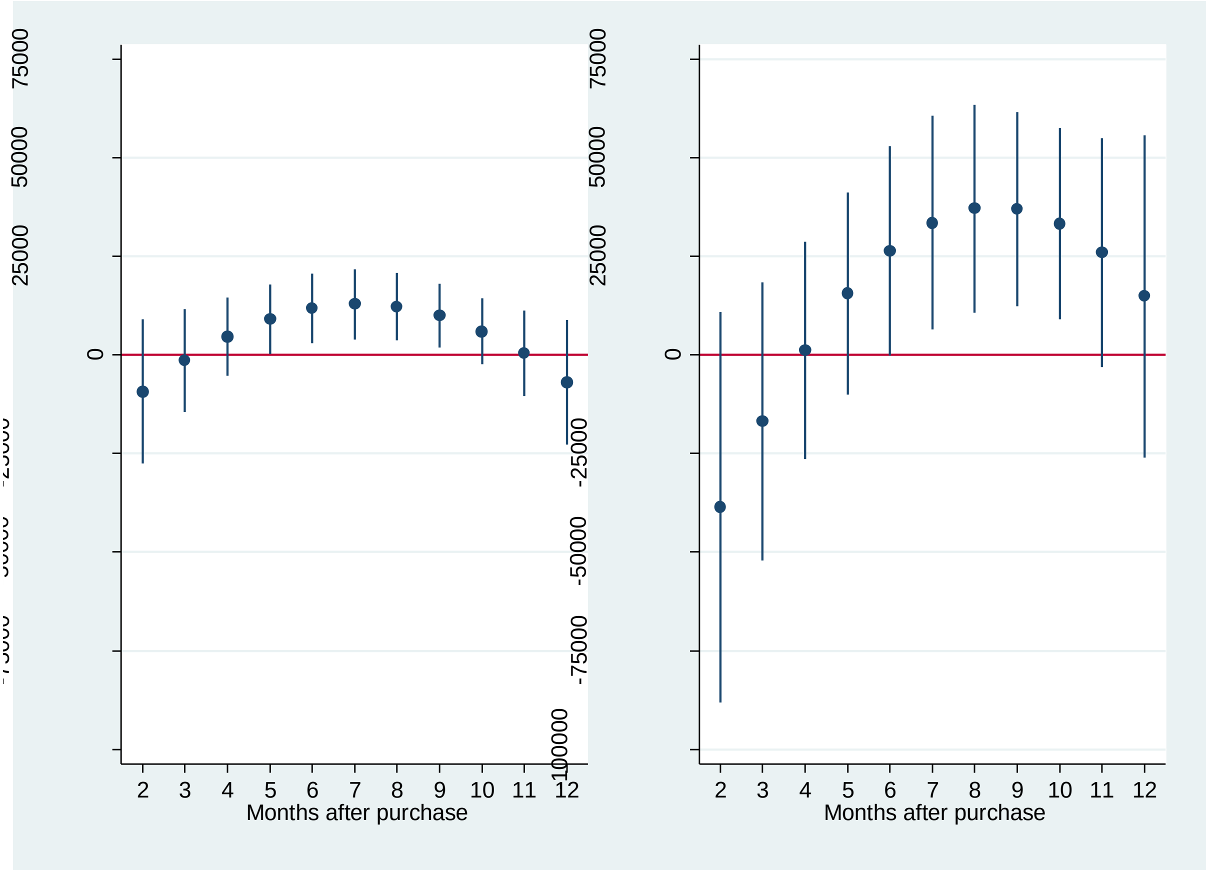
[13] 90+118 + 128 + 122 + 100 = 558

[14] 558 × 12 × 96 = 642,816.

[15] 2,220,000 + 643,000 = 2,864,000.

[16] In the right-hand panel, the month 11 estimate is significant at the 10 per cent level (see Table 1b).

Figure 3. The sales effects of sustained increases in Established Customer NPS



Computed using Stata's "matrix input" command and the user-written programme *coefplot*; the syntax is available upon request.

6 Conclusions

Our findings suggest that stores' sales respond positively to an increase in NPS. We find that the store's own Established Customer Net Promoter Score has a positive and economically meaningful effect on the store's own sales. Additionally, we find that the Net Promoter Scores of other stores in the area have a positive effect on a store's sales revenue. While the sales impact of the surrounding stores' average NPS is much larger than the impact of the store's own Established Customer NPS, both effects unfold over a period of several months (five and six months for own and area average NPS, respectively) and are quadratic, i.e. at first strengthening and then declining.

The quadratic pattern suggests that (i) the recommendation diffusion process is unlikely to begin immediately post purchase or even in the following month but is likely to take place subsequently over a period of several months; (ii) recommendations become increasingly persuasive over time as it is likely that experience of the product lends authority to a customer's recommendations to their social networks; (iii) the number of recommendations per existing customer per period will eventually decline as the purchase loses novelty and as each additional recommendation reduces the remaining number of potential recommendations within a given social network.

We set out to investigate (i) when and (ii) by how much sales will increase as a result of an increase in NPS. Our findings show that (i) a store's own NPS starts to impact a store's sales five months after product purchase while the area average NPS starts to impact a store's sales six months post purchase. In addition, we find that (ii) a sustained one percentage point (pp) increase in NPS across all UK stores corresponds to approximately a 0.5% increase in the company's annual revenue. In financial terms, for DFS, this means that a one pp increase in NPS in each of its UK stores would result in an additional £3 million of company sales revenue per year. To put this in perspective, the additional annual sales revenue as a result of a one pp increase in the NPS amounts to more than the equivalent of an average infill store's annual profit. In other words, more profit is generated by a one pp increase in NPS than by opening a new store, without having to invest the capital expenditure (on average, £1m is required to open a new store) (DFS, 2015; p.97). This makes attempts to increase NPS particularly appealing to practitioners.

Our study is based on a single company albeit a market leader. Thus, at best, we can generalise our findings to the living room furniture market. Therefore, more micro-level data must be collected from other industries and parts of retail to investigate whether the relationship (in terms of pattern, size and timing) between sales and NPS that we identified in this study is present in other sectors of the economy.

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Appendix 1: Descriptive details for the Established Customer NPS Bias-corrected LSDV regression sample

Estimation sample xtlsdvc

Number of obs = 728 (after allowing for observations lost by lagging)

Variable	Mean	Std. Dev.	Min	Max
SALES	785948	363666	174711	2031387
L1.SALES	790234	366530	174711	2031387
Z0_10_~C_bal	2.35	1.61	-3.04	8.06
Z1_10_~C_bal	11.69	9.62	-28.50	43.66
Z2_10_~C_bal	81.96	75.40	-222.28	322.06
Z0_10_~n_bal	2.14	0.69	-0.25	5.80
Z1_10_~n_bal	10.47	3.90	-4.43	28.33
Z2_10_~n_bal	72.61	30.62	-49.33	208.61
Month_20 - Month_44	0.04	0.19	0.00	1.00

For comparison: estimation on the full, unbalanced dataset for the same period (all 96 stores, with the number of monthly observations per store varying between three and 33 and an average of 20.53).

Estimation sample xtlsdvc

Number of obs = 1,971

Variable	Mean	Std. Dev.	Min	Max
SALES	690049	314290	142657	2324906
L1.	688907	313432	141147	2324906