

Sales grew 1.9%. Repeat business weakened.

New buyers kept revenue moving, while returning customers spent less. This Growth Check shows where to look, which customers to contact first, and which actions to test.

Independent sample using historical public data. Not a client engagement. A standard Growth Check includes the report, a metrics sheet and up to five ranked actions. The live dashboard and the churn model shown here are extras.

Business: UK online gift and homeware shop, mostly selling to other businesses

Data: 1.07 million order lines, December 2009 to December 2011

Prepared by Dunwell Insights, October 2026

This sample also shows: the live dashboard (a paid extra), the full at-risk list, cleaned data and scripts



New buyers covered for weaker repeat business

£9.33m Net revenue, year to Nov 2011 +1.9% on the year before	18,957 Orders -4.0% on the year before	64% Of last year's customers bought again 1,531 of 4,239 did not	£586k Last-year spend of at-risk customers 1,193 customers, each one named
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What we found

- 1

Growth came from new buyers.

Customers who left took £1.02m with them and those who stayed spent £548,000 less. New customers and guests added £1.74m.
- 2

Customers first won in autumn return less often.

48% of customers won in September to November came back within six months, against 58% for the rest of the year. The gap holds for every type of customer.
- 3

One-order customers rarely come back.

Only 39% of one-order customers came back the next year, against 77% of those with two or more. First order size and the first product bought both go with who returns.
- 4

1,193 active customers look likely to stop buying.

They spent £586k in the last year. We name every one and split them into new buyers, lapsed regulars and occasional buyers, because each needs a different follow-up.
- 5

Saturday sales are very low in the records.

£9,803 in two years, against £1.79m on Sundays.

What we'd test first

Three actions, each sized from the shop's own numbers with one stated assumption: working the at-risk list (about £35k a year), a second-order follow-up (about £34k a year) and an autumn welcome for new buyers (about £32k a year). They reach some of the same customers, so we don't add them up. Each gets tested against a hold-out group before anyone relies on it. Section 6 sets out the assumptions.

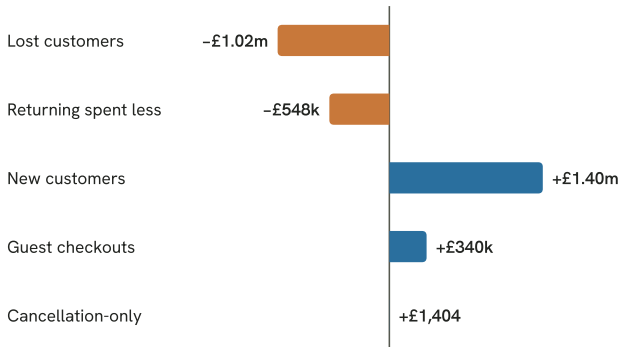
1 · WHAT HAPPENED

Existing customers took £1.57m away, and new buyers just covered it

Net revenue (sales minus cancellations) rose from £9.16m to £9.33m. That small rise is the sum of four large movements. Customers who stopped buying took £1.02m with them. Customers who stayed spent £548,000 less. New customers and guest checkouts brought in £1.74m. Take out the new customers' spending and year 2 comes in 13% below year 1.

What moved revenue from year 1 to year 2

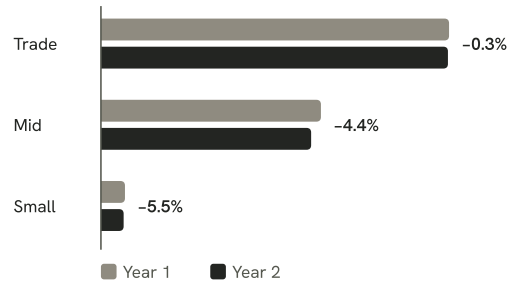
Change in net revenue, £. Each customer counted once.



Lost: bought in year 1 only. Returning: bought in both years. New: year 2 only. Guests have no account, so they get their own line, as do 23 accounts that only ever cancelled (+£1,404). With that line the movements add up exactly.

Every customer type spent less in year 2

Net revenue by customer type, £

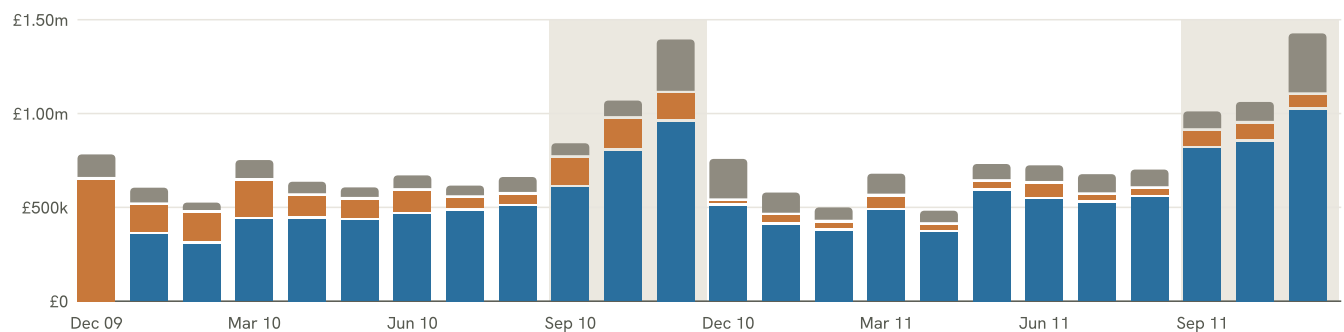


Type comes from each customer's typical order: Small under £150, Mid £150 to £400, Trade over £400. None grew.

Both years had the same shape: quiet to Easter, flat through summer, then a climb to a November peak. September to November carried 37.5% of year 2 revenue. That peak matters for the next finding.

Peak season carries more than a third of the year

Returning customers (blue), New customers (first month) (orange), Guest checkout (grey)



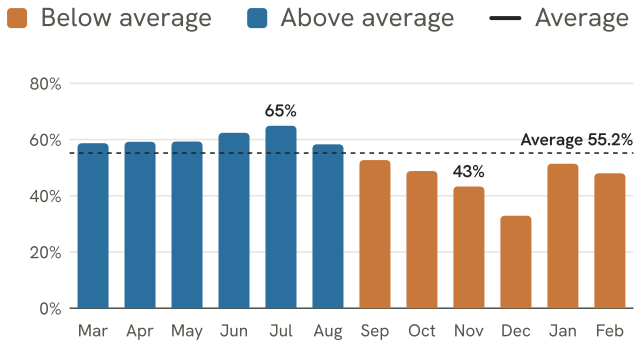
Net revenue by month. Peak season is shaded. December 2009 is the first month of data, so everyone counts as new that month. That month, new customers' cancellations outweighed their sales by £3,578. The small negative amount isn't drawn, but it is in the month's total.

2 · FINDING

Customers won in the autumn rush come back far less often

We followed every new customer from March 2010 to early June 2011 for 180 days after their first order. Of the 940 who first bought in September to November, 47.9% came back. Of the 2,310 who first bought at any other time, 58.2% did. The likely ranges (45% to 51%, and 56% to 60%) do not overlap, which supports a difference in this sample; it does not establish why the groups differ. December is weaker still: only 33% of December 2010 newcomers came back, though that group is small.

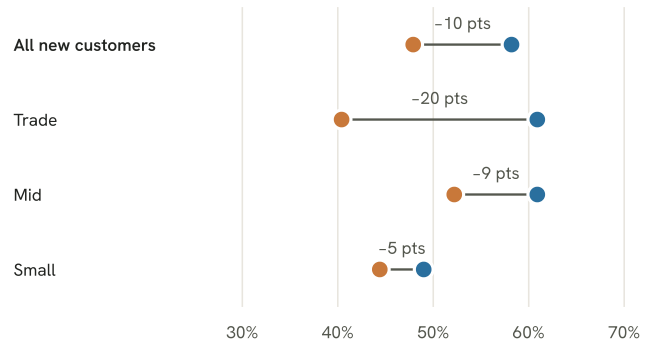
Return rate by the month a customer first bought



Share placing a second order within 180 days. First orders from March 2010 to early June 2011.

The gap holds inside every customer type

- First bought Dec to Aug
- First bought Sep to Nov



So it isn't only that autumn brings smaller buyers. Trade buyers won in autumn return 20 points less often.

Why it matters: the season that brings the most new customers brings the least loyal ones. Our reading is that many peak-season buyers come for a one-off gift order, and nothing in the shop's process treats them differently. That's a lead to test, not a proven cause.

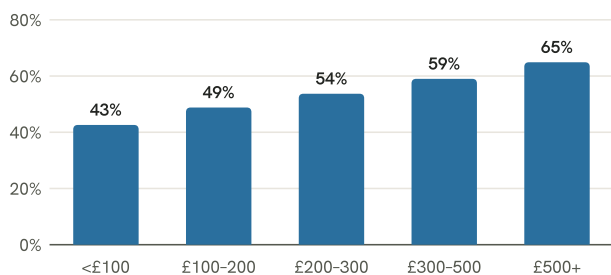
3 · FINDING

Customers who place a second order are far more likely to stay

1,426 customers ordered just once in year 1. Only 39% came back in year 2, against 77% of customers who had ordered twice or more. Two things go with coming back. The first is the size of the first order: 43% return after a first order under £100, rising to 65% after one over £500. The second is what was in it. Customers whose first order included the woodland tissues came back 78% of the time, against 43% for the vintage airline bag. These are associations. They show what to test, not proof that a bigger first order causes loyalty.

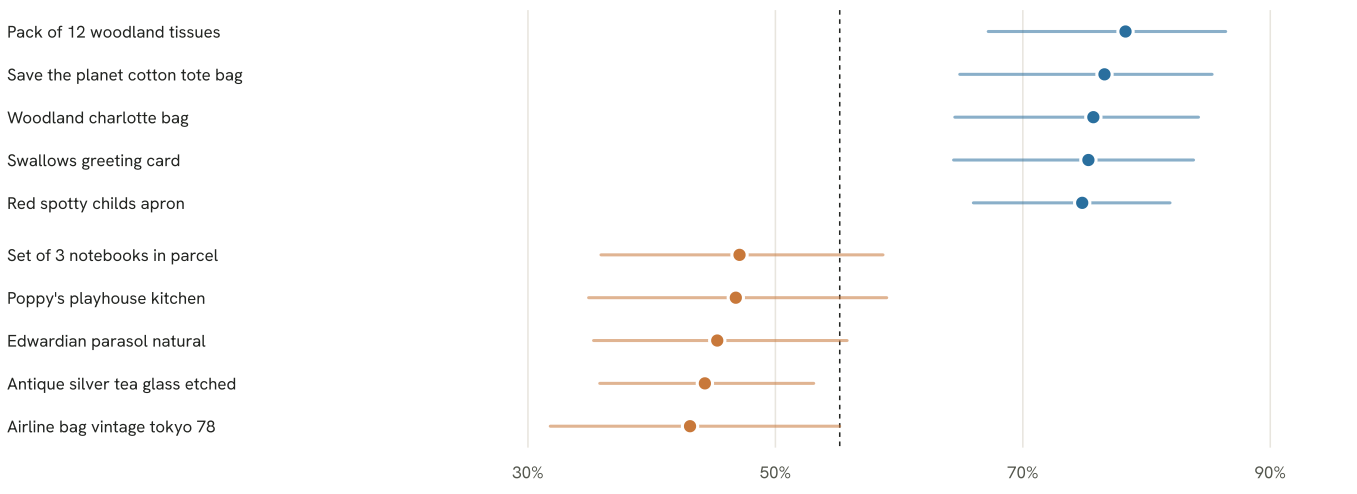
Bigger first orders go with higher return rates

Share returning within 180 days, by value of the first order



Some first products go with higher return rates

Return rate for customers whose first order included the product, with its likely range (95%)



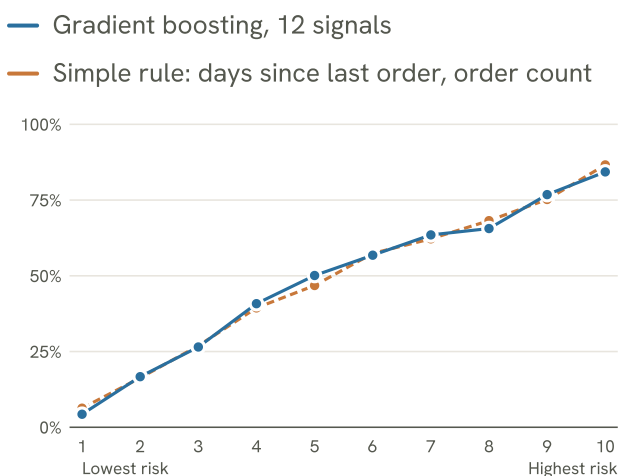
Products bought first by at least 60 customers. Woodland and children's lines lead. Gift boxes and one-off decorative pieces trail.

4 · FINDING

1,193 customers holding £586k look likely to stop buying

We scored every active customer on how likely they are to place no order in the next six months. 1,004 of 4,250 score 60% or higher, and an overdue check adds 189 regulars who have gone quiet. Together the 1,193 spent £585,751 in the last 12 months, 7.4% of all spend by active customers. That is what's at stake, not money a campaign is sure to win back. In testing, 87% of the tenth the rule rated riskiest really did stop buying, against 6% of the safest tenth.

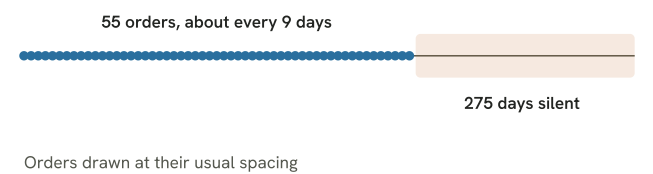
A simple rule ranks customers as well as machine learning



Customers sorted into ten equal groups by predicted risk, tested on a later period (customers as they stood on 1 June 2011). The line shows how many really stopped buying.

The lost regular

Customer 13093 ordered 55 times, usually every 9 days. Then nothing for 275 days.



The simple rule alone scores this customer at 3%, because 55 past orders pull the score down. The overdue check catches it. A monthly sales total would never show it.

We tested a gradient boosting model with twelve signals against a simple rule using two: days since the last order, and how many orders the customer has placed. They scored the same (AUC 0.787 and 0.786). We use the simple rule for every score in this report, because the owner can understand it, check it and run it in a spreadsheet. It has one weakness: many past orders pull the score down, so a heavy regular who suddenly stops still scores low. So we add one plain check. A customer with 3 or more orders who usually orders at least every 60 days, and has now been silent for four times that gap and at least 90 days, is flagged too. In testing, 55% of the customers it caught stopped buying, against 49% overall. With both, the list caught 78% of the customers who really left.

Three kinds of at-risk customer, three different follow-ups				
Group	Customers	Spend, last 12 months	Median days quiet	Follow-up
New buyer	684	£246,033	110	A thank-you and a reason to reorder, pointing to the products that go with repeat buying
Lapsed regular	281	£247,415	217	A personal call or email from the owner asking what changed, biggest spenders first
Occasional buyer	228	£92,303	210	A light check-in timed to their usual gap. No discount by default.

New buyers have ordered once. Lapsed regulars used to order at least every 90 days. Occasional buyers order less often than that, so a long gap is normal for them and the follow-up should be light.

The ten biggest at-risk customers						
Customer	Group	Risk	Spend, last 12 months	Days since last order	Orders	Usual gap
15749	Lapsed regular	Overdue	£21,536	235	3	Every 48 days
16180	Lapsed regular	Overdue	£10,217	100	13	Every 20 days
12590	New buyer	79%	£9,338	211	1	One order so far
12980	Lapsed regular	Overdue	£7,092	157	21	Every 27 days
13093	Lapsed regular	Overdue	£6,942	275	55	Every 9 days
13027	Lapsed regular	Overdue	£6,912	113	19	Every 27 days
12688	New buyer	75%	£4,874	113	1	One order so far
12752	New buyer	73%	£4,367	81	1	One order so far
12536	New buyer	71%	£4,151	59	1	One order so far
12378	Occasional buyer	64%	£4,009	129	2	Every 432 days

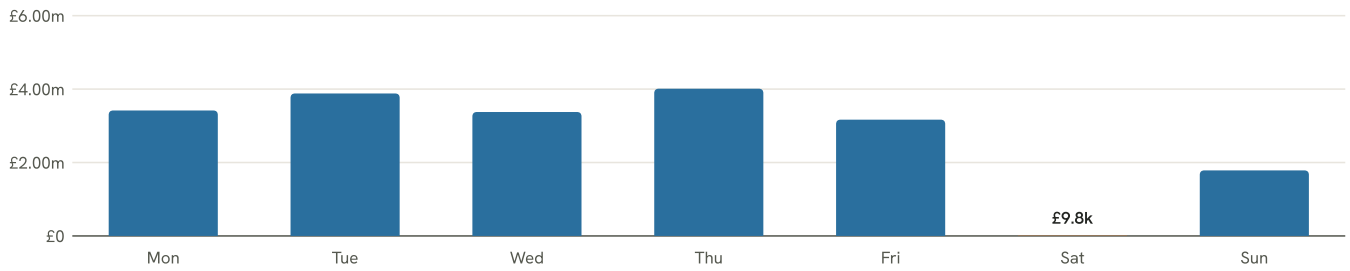
All 1,193 are in the dashboard and in at_risk_customers.csv, delivered with this report.

5 · FINDING

Saturday sales are very low in the records

Across two years, the records show £9,803 of Saturday sales. Sundays brought in £1.79m. Orders peak at midday and almost stop after 6pm. That fits a shop selling mostly to other businesses. The order records can't say whether customers try to order on Saturdays and give up. Website visits and Saturday enquiries would answer that.

Sales by day of the week, both years, before cancellations



6 · ACTIONS

What to test, what it could be worth, and how we'll know

Each value is yearly revenue, estimated as one stated assumption times the shop's own numbers. Spend uses medians, so a few huge trade accounts don't inflate the result. The actions reach some of the same customers, so these are separate scenarios. They are not added together.

Action	Based on	Assumption	Yearly value, estimated	Effort
Work the at-risk list every week. Follow up by group: second-order offer for new buyers, a personal call for lapsed regulars, a light check-in for occasional buyers.	1,193 customers. The median one spent £291 last year.	One in ten keeps buying, about 119 customers, each spending that median	£35k	Low. A weekly list and an hour of calls.
Second-order follow-up. Follow up every first order within 30 days with a reason to reorder. Point first orders towards the products that go with repeat buying.	1,426 one-order customers a year, 39% return. A returner spends a median £400 the next year.	Return rate up 6 points, about 86 more customers	£34k	Low. One automated email sequence.
An autumn welcome for peak-season buyers. Treat September to November first orders as their own group, with a January follow-up planned before the season starts.	940 autumn newcomers, returning 10 points less often. A returner spends a median £654 in their first year.	Half the gap closed, about 48 more customers	£32k	Medium. Planned by August.
Check Saturday demand. Look at Saturday website visits and enquiries before deciding anything.	£9,803 of Saturday sales in two years	None yet. This is a question to answer first.	Not sized	Low

Why there's no total: 684 of the at-risk customers are new buyers, who the second-order follow-up would also reach. 656 of the 940 autumn newcomers ordered only once, so they are second-order targets too. Adding the three figures would count some of the same customers twice. The hold-out groups below will show the real combined effect.

How we'll measure it: for each action, hold back one in five of the customers it targets and leave them alone. The action list marks them. At 90 days, compare the two groups for an early read. The main result comes at 180 days for return rate and at 12 months for spend, the same periods the estimates use. The measured difference replaces our estimate.

Every step and every decision, so you can check our work

The analysis runs from the raw file to this report with one command. The scripts, the cleaned data and the full at-risk list come with the report, so every number here can be traced and rerun.

Cleaning the data		Checks we ran	
Rows in the raw file	1,067,371	• The revenue bridge adds back to the year totals exactly, once 23 accounts that only ever cancelled get their own line (+£1,404). • Two separate scripts count the customers in each year (4,239 and 4,293) and agree. • Every rate comparison carries a 95% range (a Wilson interval). We only call a difference real when the ranges don't overlap. • The autumn finding was rerun inside each customer type, to rule out a change in the mix of customers. • The model was tested on a later period than it was trained on, the way it would be used in practice, and compared against a simple rule. • Every risk score in the report, dashboard and customer files comes from the same method: the simple rule plus the overdue check. • Our own review of the draft caught one error: the customer counts behind the month-by-month return chart were five times too high. The rates were right. The counts are fixed.	
Exact duplicate rows	-34,335		
Postage, fees and manual adjustments	-5,718		
Zero-price lines and stock write-offs	-5,986		
Rows used	1,021,332		
of which cancellations, kept as negative revenue	17,915		
of which guest orders (no customer number)	227,167		

Decisions log

Decision	Why	Effect
Count cancellations as negative revenue, not delete them	A large order that was later cancelled is not a sale. One order for 74,215 storage jars was cancelled the same day.	17,915 lines, £716k taken off sales across the data
Remove exact duplicate rows	The same line recorded twice would double-count sales.	34,335 rows removed
Remove postage, fees and adjustments	They are not products, and they distort product and order figures.	5,718 rows removed
Keep guest orders in revenue but not in customer analysis	The money is real, but without a customer number a guest can't be followed over time.	227,167 rows. Guests are 15% of year 2 revenue.
Compare full 12-month years, December to November	The data ends on 9 December 2011, so a calendar-year comparison would be unfair.	The partial December 2011 is left out of year-on-year figures
Start return and cohort analysis in March 2010	Customers first seen in the first three months may have bought before the data starts, which would flatter their return rate.	December 2009 to February 2010 newcomers left out
Give every customer a full 180 days to return	A customer who joined last month hasn't had the chance to come back yet.	First orders after 10 June 2011 left out of return rates

Decision	Why	Effect
Set customer type by typical order size, not total spend	Total spend grows with time, so it mixes up loyal small buyers and big new ones.	Small, Mid and Trade, based on the median order
Test the model on a later period, not a random sample	A random split lets the model peek at the future. Real use always predicts forward.	Trained at 1 Dec 2010, tested at 1 Jun 2011
Score with the simple rule, not machine learning	Same accuracy, and the owner can check it.	Accuracy scores (AUC) 0.787 and 0.786
Add an overdue check for regulars	The rule scores heavy regulars low even when they stop. Customer 13093 scored 3%.	189 more customers flagged
Split the at-risk list into three groups	A customer who ordered once last month needs something different from a regular who went quiet.	New buyers, lapsed regulars, occasional buyers
Show the actions as separate scenarios, not a total	They reach some of the same customers, so adding them would double-count.	Each one sized and tested on its own
Use medians for the value of each action	A handful of very large trade accounts would inflate an average.	Lower, safer estimates

What the data can't tell us

- There are sales but no costs, so this report is about revenue, not profit.
- There is no marketing, website or stock data. Where we suggest a cause, it's a lead to check, not a proven fact.
- About 15% of year 2 revenue came from guest checkouts, which can't be followed over time.
- Risk scores rank customers well. Treat the exact percentage as a guide, not a promise.
- Last year's spend shows what's at stake. It isn't money a campaign is sure to win back.
- Findings about first orders, products and seasons are associations. They point to what to test, not proof of cause.
- This is one shop's data. The methods carry over to other businesses. The specific numbers don't.

This analysis is based on the data supplied and the methods described here. It is there to support decisions. It is not a promise of any result, and it is not financial, legal or tax advice.

Every job. Done well.

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Data: Chen, D. (2019). Online Retail II. UCI Machine Learning Repository, CC BY 4.0. archive.ics.uci.edu/dataset/502