Head of Analytics Handy Practical

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Logging Requirements for Prepay Promotion

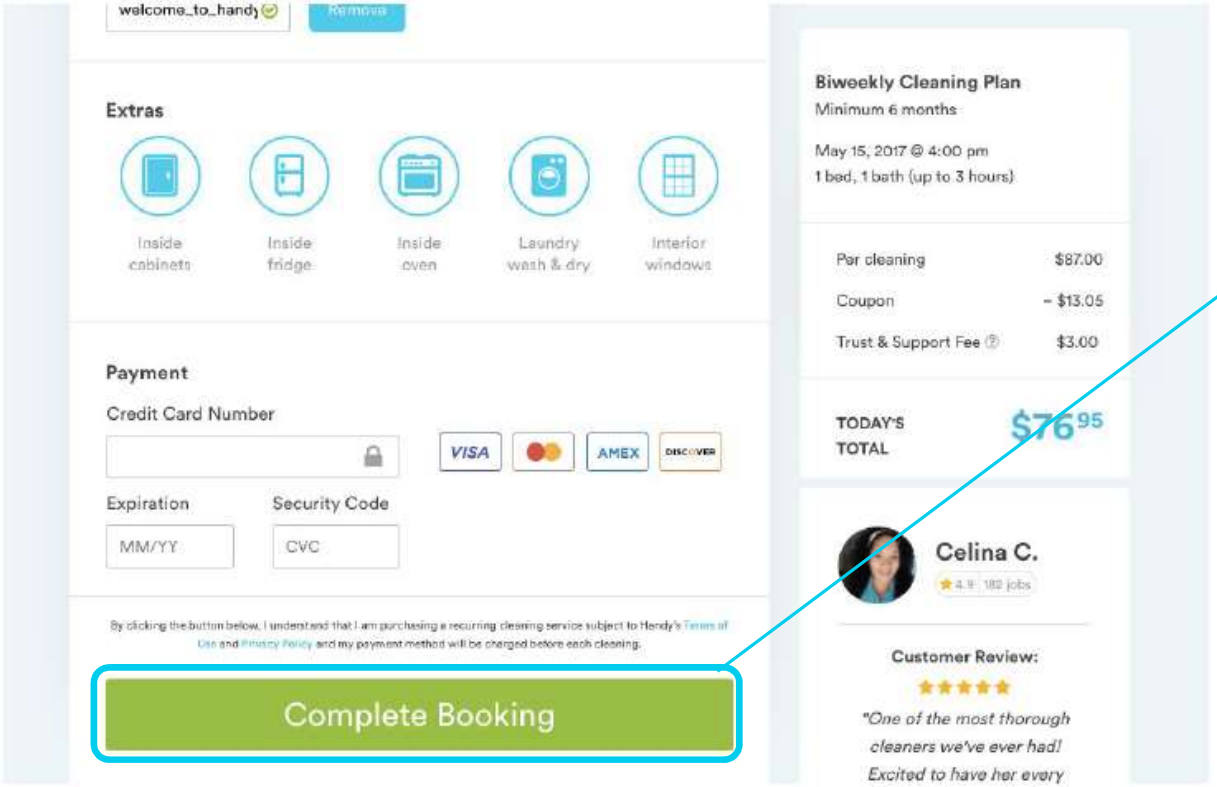
What events need to be tracked to measure success?

We can use a simple taxonomy to measure success against our goals for acceptance and cancellation rates

Properties

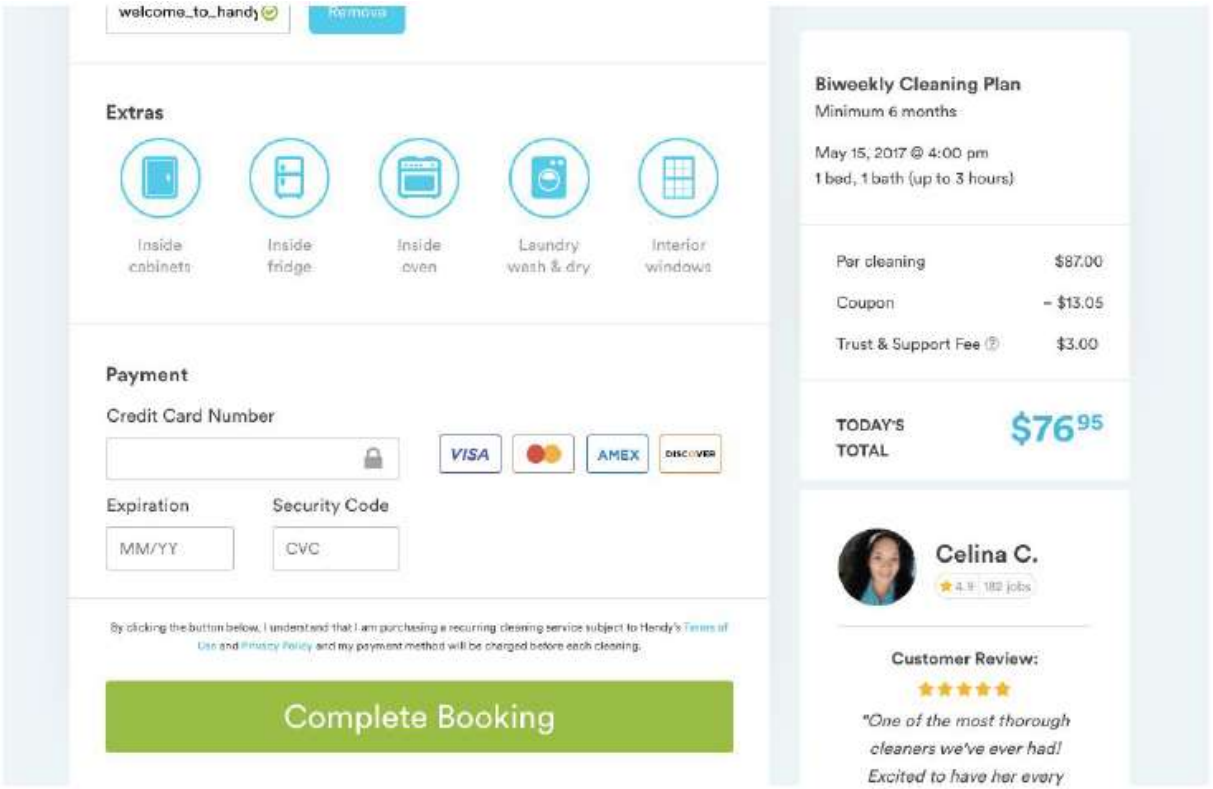
modal_view	button_click	transaction_submit
timestamp: [local time when the event occurred]	timestamp: [local time when the event occurred]	timestamp: [local time when the event occurred]
element_id: [unique ID for the involved element, e.g. button, modal etc.]	element_id: [unique ID for the involved element, e.g. button, modal etc.]	trxn_id: [unique ID for specific transaction]
user_id: [unique ID for authenticated users]	user_id: [unique ID for authenticated users]	user_id: [unique ID for authenticated users]
session_id: [unique ID for the current session]	session_id: [unique ID for the current session]	session_id: [unique ID for the current session]
experiment_id: [unique ID for an A|B or multivariate test]	experiment_id: [unique ID for an A|B or multivariate test]	failure_code: [unique ID for the reason of transaction failure; null = success]
		trxn_type: (‘mopconfirm’,'first', 'recurring', 'prepay', 'onetime', 'cancel', 'terminate‘)
		plan_id: [unique ID for the service plan involved in the transaction; not a SKU]

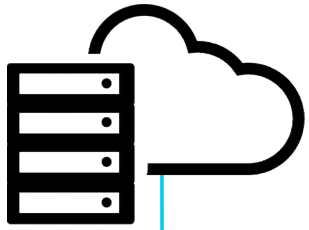
The primary event of interest on the Payment Page is the click_event when a user signs up for a cleaning plan




```
analytics.logEvent("button_click", {
    timestamp: "2019-08-16 10:43:19 UTC"
    element_id: completebooking123
    user_id: user456
    session_id: session789
    experiment_id: incumbent987
    })
```

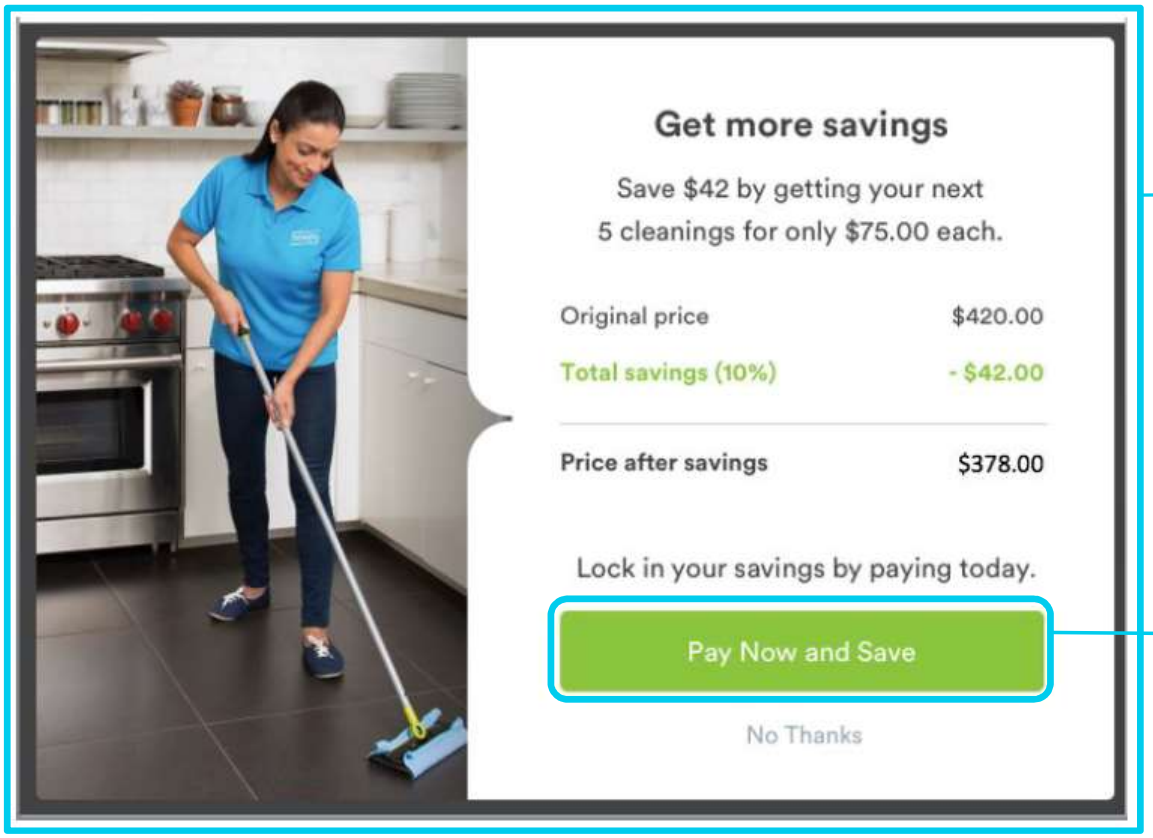
Additional events can be logged server-side once the button click triggers a transaction to be processed





```
analytics.logEvent("transaction_submit", {
    timestamp: "2019-08-16 10:43:20 UTC"
    user_id: user456
    session_id: session789
    failure_code: null
    trxn_type: 'first'
    plan_id: plan654
    })
```

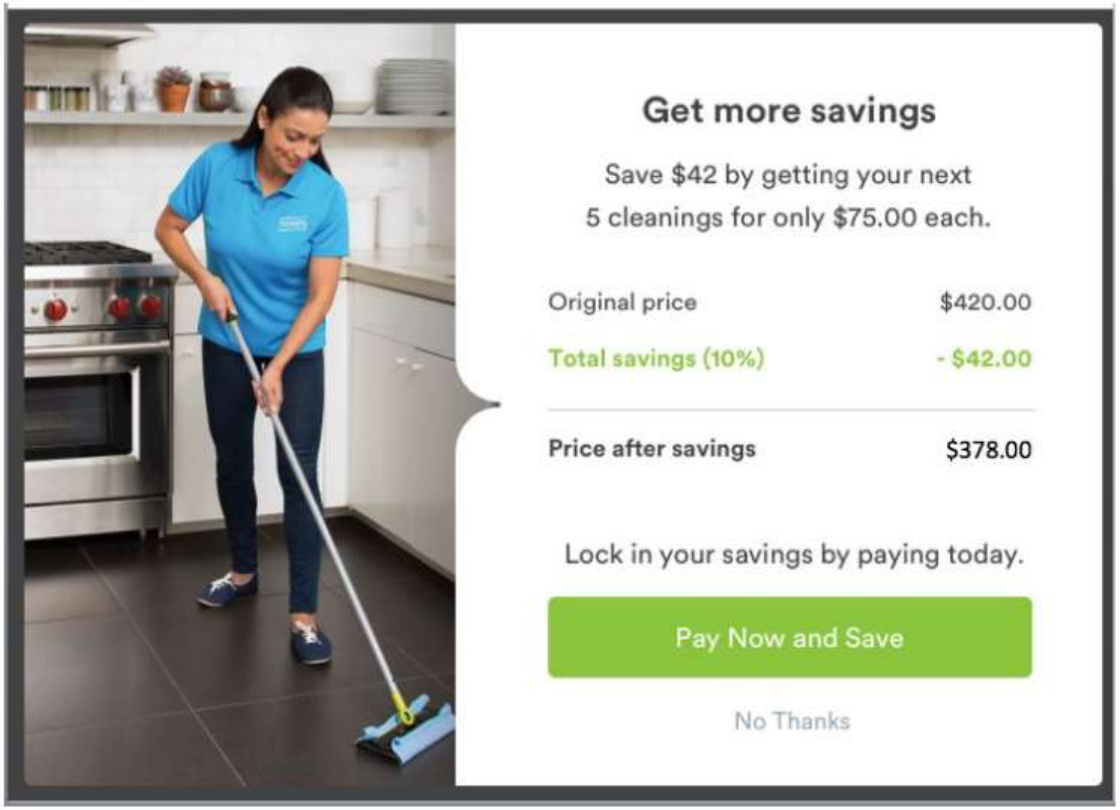
Once the modal loads, we will want to log a modal_view event and then a button_click event when the offer is accepted

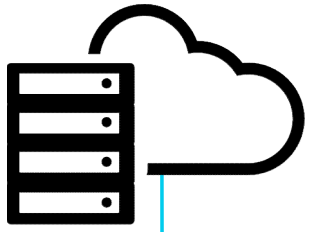



```
analytics.logEvent("modal_view", {
    timestamp: "2019-08-16 10:43:21 UTC"
    element_id: prepaymodal123
    user_id: user456
    session_id: session789
    experiment_id: variant987
    })
```

```
analytics.logEvent("button_click", {
    timestamp: "2019-08-16 10:43:30 UTC"
    element_id: acceptoffer123
    user_id: user456
    session_id: session789
    experiment_id: variant987
    })
```

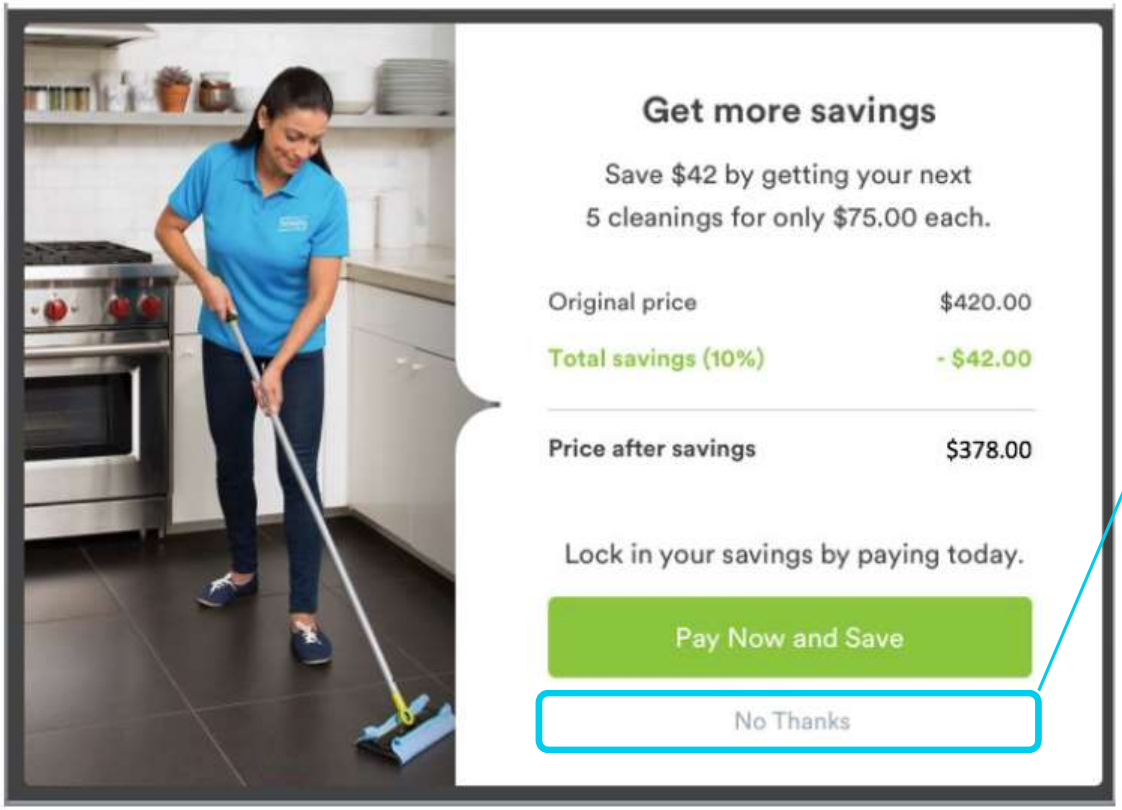
Again server-side events should be logged to confirm a payment was processed successfully





```
analytics.logEvent("transaction_submit", {
    timestamp: "2019-08-16 10:43:31 UTC"
    user_id: user456
    session_id: session789
    failure_code: null
    trxn_type: 'prepay'
    plan_id: plan654
    })
```

Finally, we want to log a button_click event whenever a user declines the prepay offer




```
analytics.logEvent("button_click", {
    timestamp: "2019.08.16.10.43.20.60"
    element_id: declineoffer123
    user_id: user456
    session_id: session789
    experiment_id: variant987
    })
```

With these 3 events and their related properties, we can report on all of the desired KPIs for the prepay offer

- **Total daily users making a cleaning plan** = daily count of unique user_ids that have logged a successful first transaction (or method of payment confirmation) for a cleaning plan
- **Total daily users shown the new modal** = daily count of unique user_ids that have logged a modal_view event
- **Count of daily users who accepted the offer** = daily count of unique user_ids that have logged an accept button_click event [1]
- **% of users who accepted the offer** = (count of unique user_ids that have logged an accept button_click event) / (count of unique user_ids that have logged a modal_view event)
- **% of users who clicked "No Thanks"** = (count of unique user_ids that have a decline button_click event) / (count of unique user_ids that have logged a modal_view event) [2]
- **Cancellation rate for users electing to pre-pay** = (count of unique user_ids that logged both a successful prepay and a cancel transaction event for the same plan_id) / (count of unique user_ids that logged a successful prepay event)

1 – Accepting an offer does not necessarily equate to a successfully completed transaction but we can reliably assume that an accept button click also triggers a successful transaction submit server-side event if the first transaction for the cleaning plan succeeded and no further steps are required of the user to process the transaction after clicking the accept button
2 – Some users who see the modal may bounce without clicking on any buttons so this metric does not necessarily reflect the true number of offer declines

FurnitureCo. Partnership

Is this the right opportunity for Handy?

Projected bookings offer a sufficient buffer to consider this project low risk and worth moving forward

Annual FurnitureCo Sales (SKU count)	6,000,000
Percent Handy Eligible	40%
Annual Eligible Sales (SKU count)	2,400,000
Attach Rate Goal	5.0%
Expected Annual Bookings	120,000
Probability of Success	30%
Probability Adjusted Bookings	36,000

- Our base case projects double the bookings required to realize a return on the expected 6 weeks of engineering time invested
- If confidence in achieving our attach rate goal on the 2.4 million eligible SKUs drops below 15%, reevaluate the partnership

If we assume that the eligible number of SKUs sold will be the same across all tiers, the expected margin easily exceeds 15%

FurnitureCo Product Retail Price Tier	% Total SKU Sold	Gross Profit/Loss
$0.00 to $99.99	22%	$ (17.00)
$100.00 to $199.99	10%	$ 3.00
$200.00 to $299.99	15%	$ 13.00
$300.00 to $399.99	6%	$ 33.00
$400.00 to $499.99	7%	$ 30.50
$500.00 to $599.99	10%	$ 40.50
$600.00 to $799.99	10%	$ 48.00
$800.00 (+)	20%	$ 85.50

In the base case scenario:

- Blended average revenue per booking = $96.70
- Blended average costs per booking = $68.13
- Blended average margin per booking = $28.58 or 29.6% of revenue

That said, the proposed service prices are much higher at lower tiers relative to product prices, which could impact attach rates

FurnitureCo Product Retail Price Tier	Service-to-SKU Midpoint Price	Expected % of Bookings
$0.00 to $99.99	7/9	7.6%
$100.00 to $199.99	2/5	9.6%
$200.00 to $299.99	2/7	17.1%
$300.00 to $399.99	1/4	7.1%
$400.00 to $499.99	2/9	8.6%
$500.00 to $599.99	1/5	12.6%
$600.00 to $799.99	1/5	12.9%
$800.00 (+)	2/9	24.5%

- Weighting the % Total SKUs Sold by (1 – (the service-to-SKU midpoint price)) and then renormalizing produces a very different distribution of bookings across tiers
- Margin goes up to 35% with a larger proportion of bookings expected to come from higher price tiers
- Higher margins may come with a hidden cost though

Handy stands to acquire more customers with a blended profit margin still over 15% by treating lower tiers as loss leaders

FurnitureCo Product Retail Price Tier	Original Proposal	Alternative Scenario
$0.00 to $99.99	$ 39.00	$ 19.00
$100.00 to $199.99	$ 59.00	$ 29.00
$200.00 to $299.99	$ 69.00	$ 49.00
$300.00 to $399.99	$ 89.00	$ 69.00
$400.00 to $499.99	$ 99.00	$ 89.00
$500.00 to $599.99	$ 109.00	$ 109.00
$600.00 to $799.99	$ 129.00	$ 139.00
$800.00 (+)	$ 179.00	$ 179.00

In the alternative scenario:

- Blended average revenue per booking = $88.29
- Blended average costs per booking = $68.60
- Blended average margin = $19.69 or 22.3% of revenue
- More analysis is required to determine if the forgone profits could be offset by cross-selling other services to newly acquired customers

To prep for our next check-in, the query below can be used to construct a histogram of ratings for FurnitureCo bookings

```
SELECT Rating_Bucket as "Rating Bucket",
count(*) as "Count of Bookings"
FROM (
  SELECT *,
    CASE WHEN provider_rating <=1 THEN
"1"
      WHEN provider_rating <=2 THEN "2"
      WHEN provider_rating <=3 THEN "3"
      WHEN provider_rating <=4 THEN "4"
      WHEN provider_rating <=5 THEN "5"
      ELSE "ERROR" END AS Rating_Bucket
  FROM tbl.Booking a
  WHERE a.booking_end_state = “3"
  AND a.partner_type = "2"
  ) b
GROUP BY Rating_Bucket;
```

- This creates 5 buckets corresponding to a rating scale of 1-5
- Cancelled bookings have been filtered out but can be added back in by modifying the WHERE clause
- To compare FurnitureCo to other booking sources for furniture assembly and TV mounting, re-run the query using WHERE a.partner_type != “2” AND a.service_id IN (“2”,”3”) AND a.booking_end_state = “3"

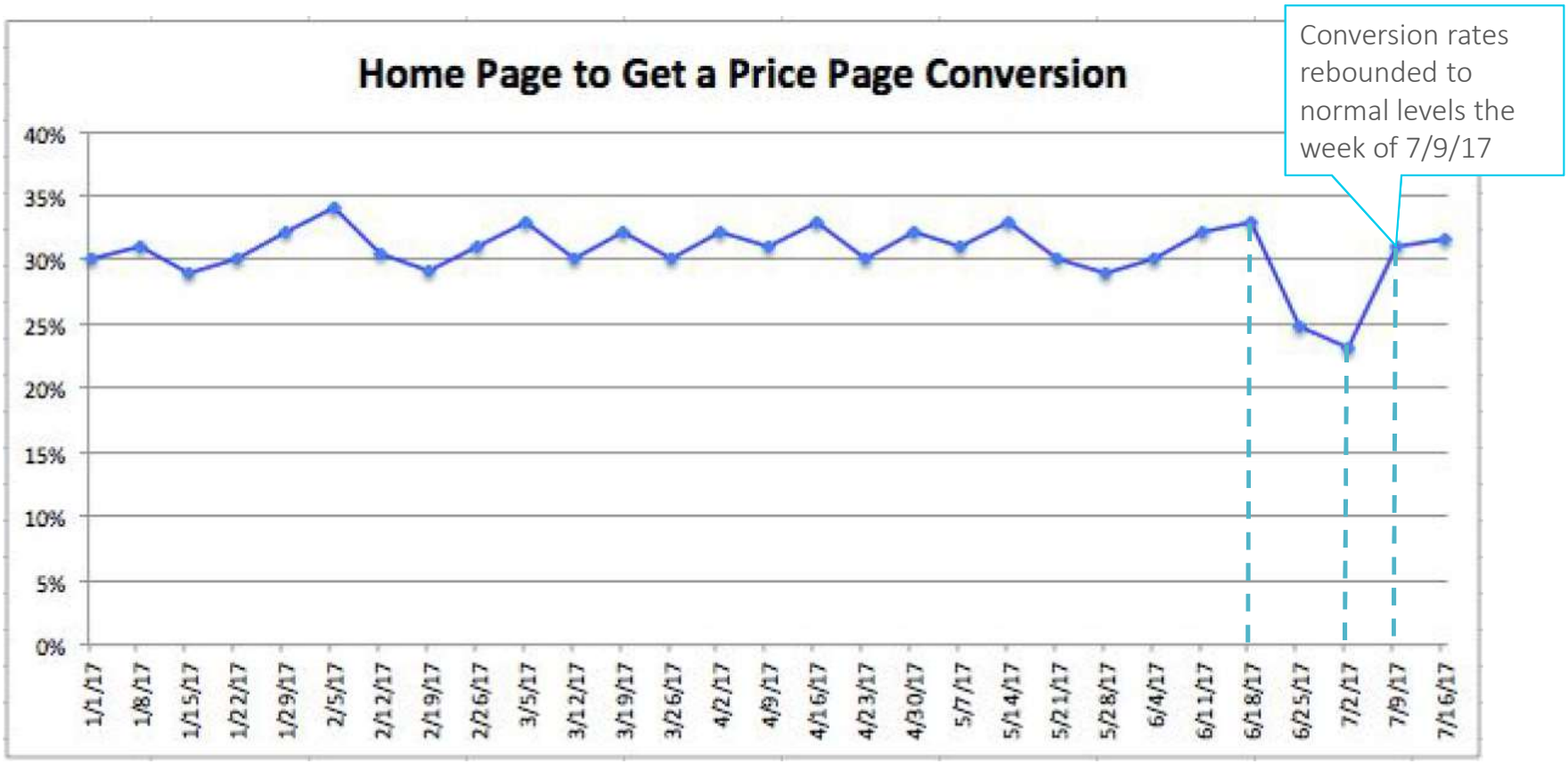
We will need to analyze much more than just ratings, however, to properly gauge our progress toward our partnership goals

- How do actual attach rates differ from expected attach rates across price tiers (assuming FurnitureCo is sharing data on offer exposures)?
- Is the distribution of total bookings across product price tiers notably different from the expected distribution based on total SKUs sold?
  - Given the actually distribution, is our blended profit margin still over 15%?
- Is there any correlation between ratings and product price tier that might be indicative of a perceived value shortfall?
- Extrapolating from the first 2 weeks, are annualized bookings projected to exceed the 18,000 threshold?
  - At the current rate, how many weeks will it take to hit 18,000 bookings?
- Of the bookings sourced through FurnitureCo, what portion are new vs. returning Handy customers?
  - What about for loss leaders in particular? Are loss leaders opening up a viable acquisition channel?
- Have we been able to fulfill at least 95% of bookings so far?
  - Does the cancellation rate vary at all across price tiers?

Conversion Rate Report

Why did the conversion rate dip?

Between the weeks of 6/18/17 and 7/2/17, conversion rates dropped precipitously from historical averages in the low 30s



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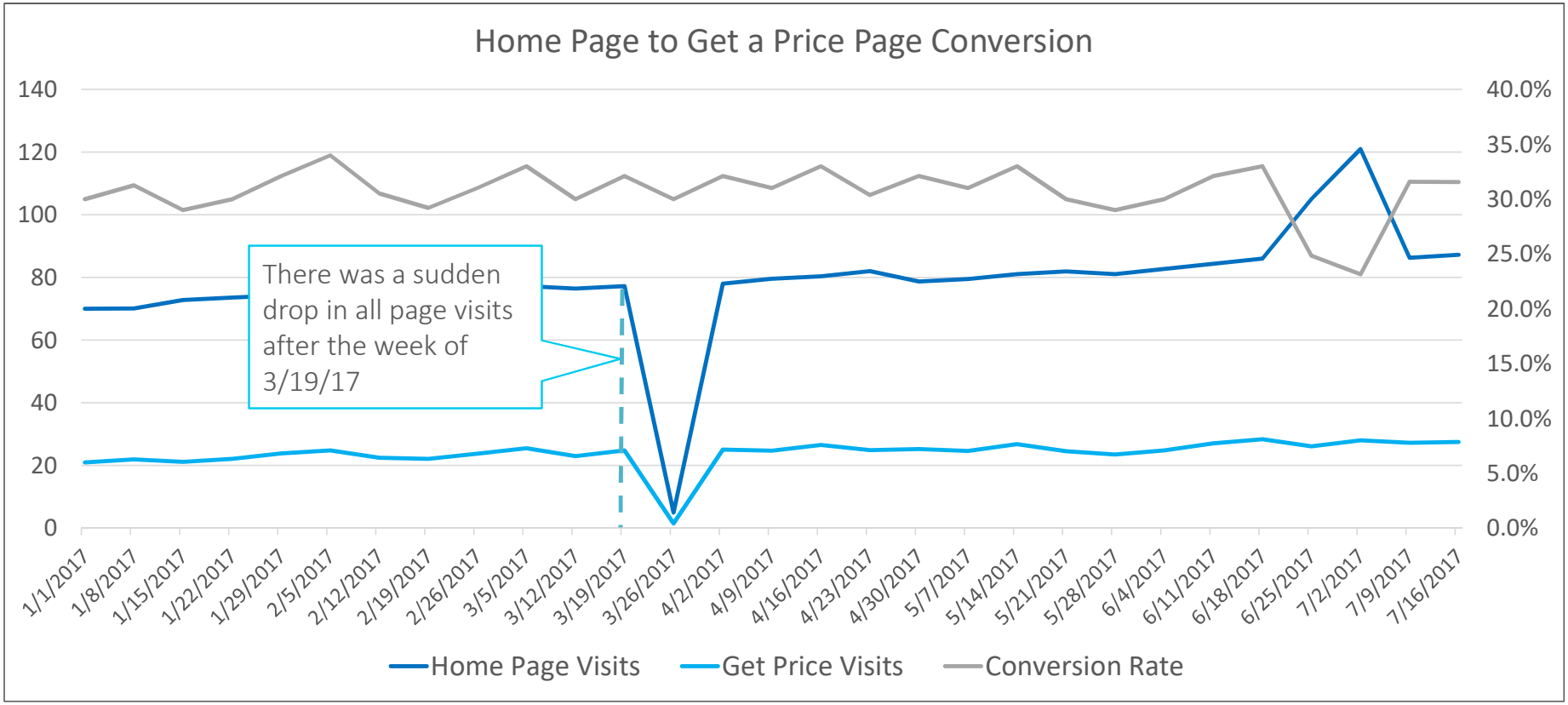
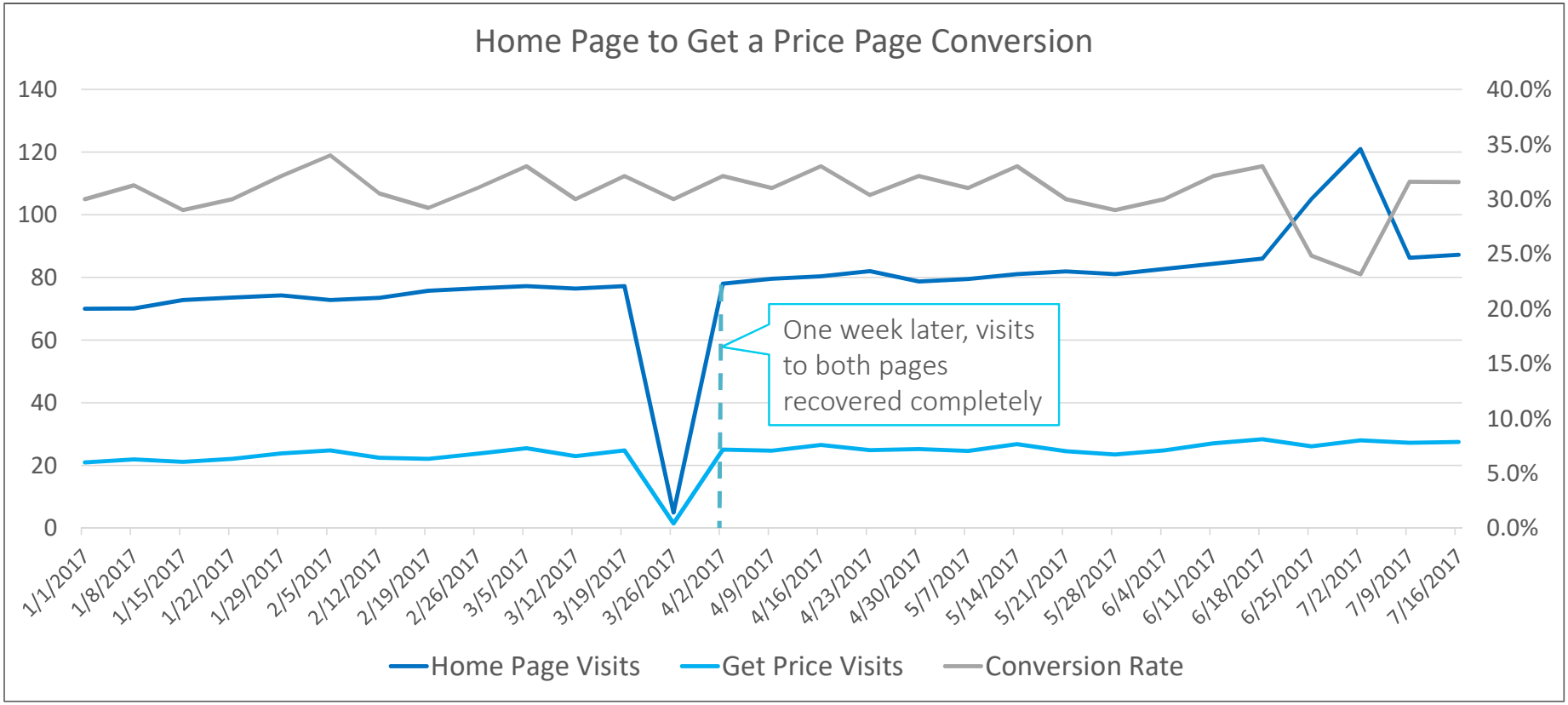
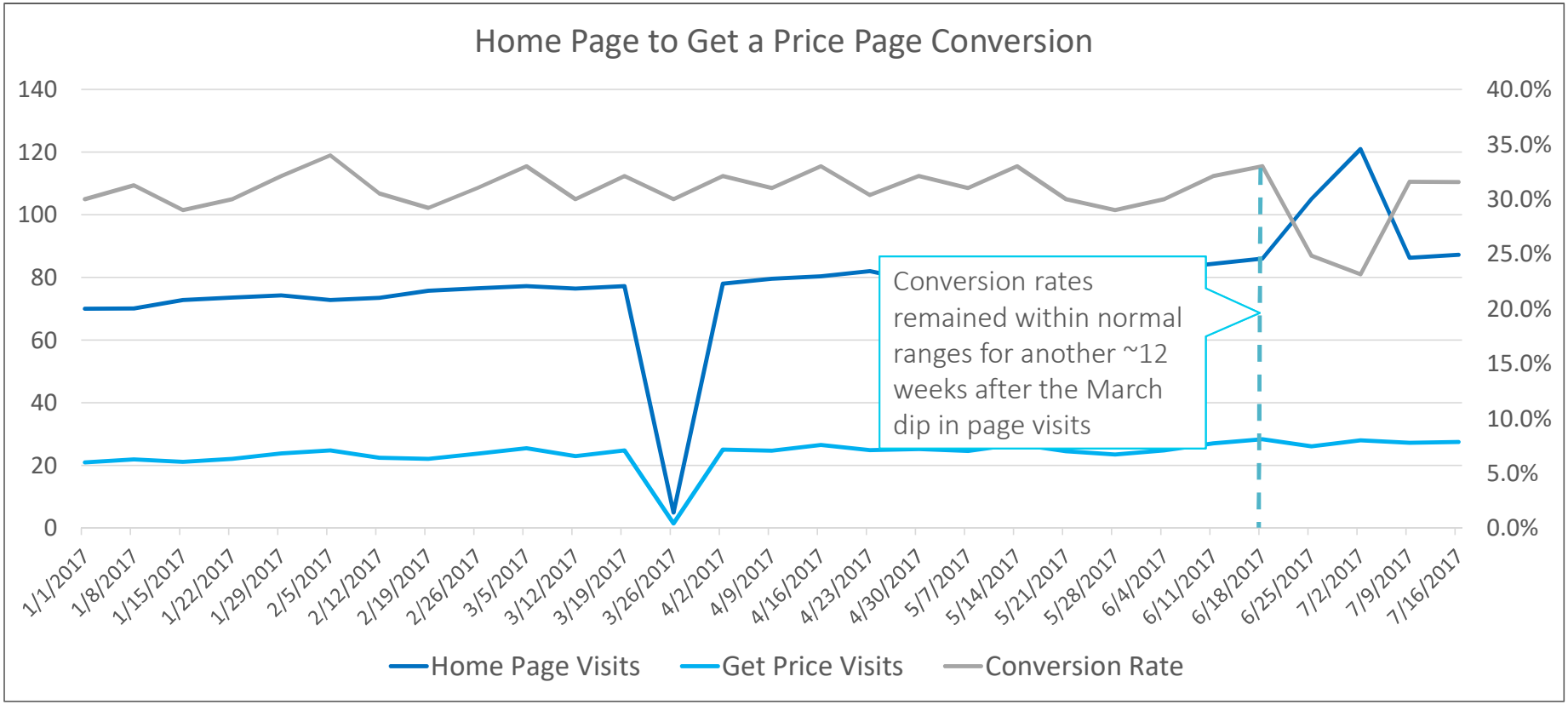
A closer look at page visits over the same period reveals there's more to the story than just a drop in the conversion rate



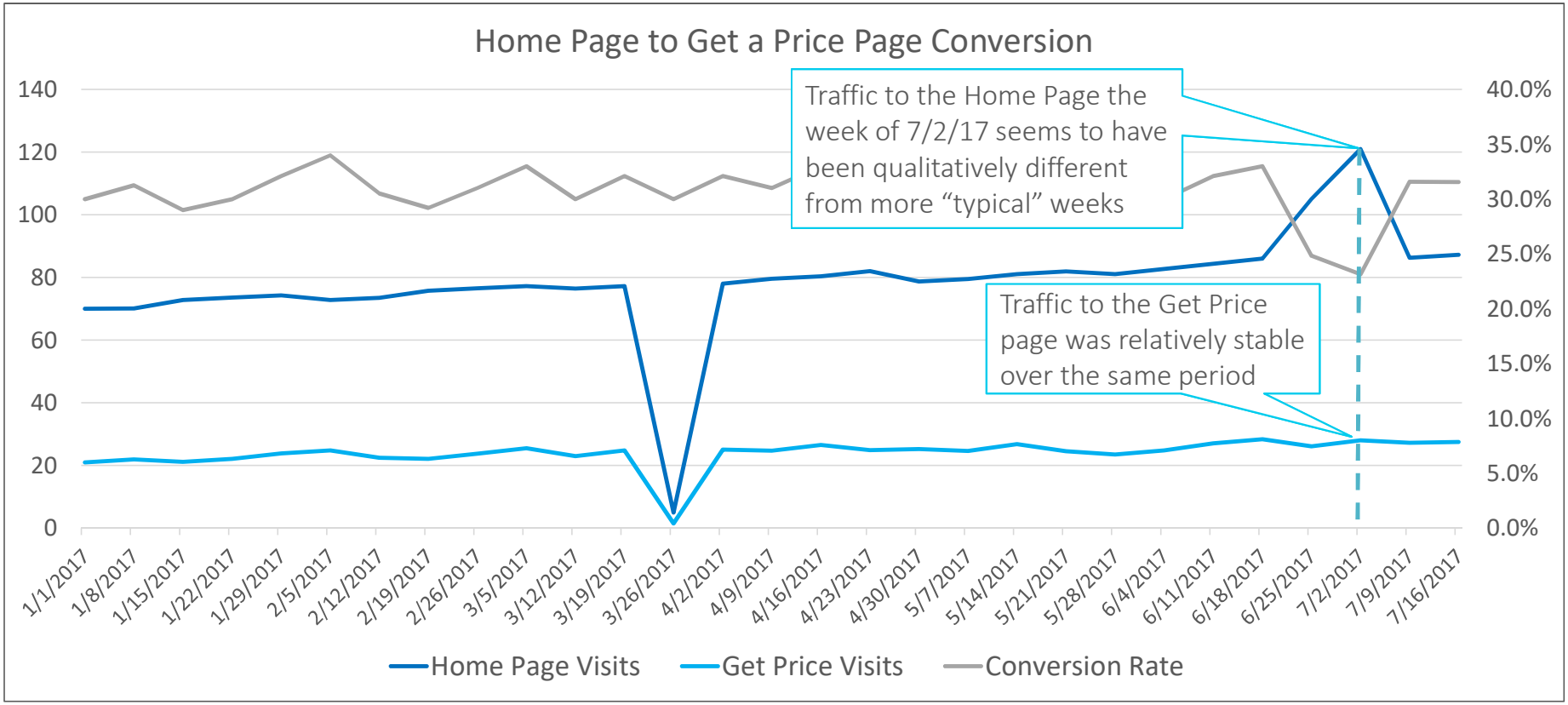
Such a sudden near complete collapse in page visits is as if the site temporarily disappeared from the internet



Nonetheless, whatever happened in March seemed to have no immediate impact on conversion rates



Rather, it was a spike in Home Page visits in July that seems to be related to the drop in conversion rates



Although we do not have enough information to draw any immediate conclusions, we have some hypotheses to work from

With regard to the drop in page visits in March

- Confirm there was not a site outage or other disruption that would have rendered pages inaccessible to visitors
- Assuming accessibility was not the cause, check to be sure visits were logging correctly and there are no data quality concerns
- If the site was accessible and visits were being logged correctly, the most likely explanation is a change in discoverability, e.g. a change in Google's search algorithms impacting Handy.com's position in search results
  - Were there any notable changes in referrals from either organic or paid search? What about paid media in general?

The most valuable next step would be to look at trends in referral sources from January to July

A change in referral sources could explain not only the March drop in visits but also the June/July spike and related dip in conversion rates

- A notable increase in referrals from paid media would suggest an ad campaign, perhaps related to the upcoming July 4th holiday, was successful in driving more traffic to the Home Page
  - Most of that incremental traffic, however, would have been lower quality leads
- Earned media, such as press coverage, could also have been behind the spike in traffic in June/July
  - If so, we should expect to see an increase in organic search referrals and also perhaps some change in Google Trends around the same time
- For good measure, we should still confirm that there were no changes to the Home Page that might have impacted navigation from the Home Page to the Get Price page

SEM and Display Marketing Analysis

What’s our return on ad spend?

Between 10/28/2018 and 11/17/2018, we spent $351,100 on Display and SEM advertising

	SEM	Display
Total Spending	$214,500	$136,600

Over the same period, there were 5,594 conversions (i.e. first time user bookings) across all channels

	SEM	Display	Non-Paid Channels [1]
Total Spending	$214,500	$136,600	$0
Last Click Conversions	1,541	264	3,789

1 – Non-Paid Channels includes Direct, Organic Search, Email and Other

On a last click basis, there was a significant difference in customer acquisition costs (CAC) between the paid channels

	SEM	Display	Non-Paid Channels [1]
Total Spending	$214,500	$136,600	$0
Last Click Conversions	1,541	264	3,789
Last Click CAC	$139	$517	N/A

1 – Non-Paid Channels includes Direct, Organic Search, Email and Other

The number of conversions influenced by an ad, however, was actually higher for Display than for SEM

	SEM	Display	Non-Paid Channels [1]
Total Spending	$214,500	$136,600	$0
Last Click Conversions	1,541	264	3,789
Last Click CAC	$139	$517	N/A
Influenced Conversions [2]	1,326	1,787	N/A

1 – Non-Paid Channels includes Direct, Organic Search, Email and Other
2 – Values are not mutually exclusive; SEM and Display could have both influenced the same conversions; a channel is considered to have influenced a conversion if, prior to the last click, the user saw a Display ad or clicked on either a Display or SEM ad one or more times ; there were 2,315 influencing SEM clicks and 4,147 influencing Display touchpoints

After applying fractional, rules-based multi-touch attribution, the difference in CAC between paid channels collapses to just $14

	SEM	Display	Non-Paid Channels [1]
Total Spending	$214,500	$136,600	$0
Last Click Conversions	1,541	264	3,789
Last Click CAC	$139	$517	N/A
Influenced Conversions [2]	1,326	1,787	N/A
Fractional Contribution [3]	1,772.7	1,014.8	2,806.5
Fractional CAC	$121	$135	N/A

1 – Non-Paid Channels includes Direct, Organic Search, Email and Other
2 – Values are not mutually exclusive; SEM and Display could have both influenced the same conversions; a channel is considered to have influenced a conversion if, prior to the last click, the user saw a Display ad or clicked on either a Display or SEM ad one or more times; there were 2,315 influencing SEM clicks and 4,147 influencing Display touchpoints
3 – Fractional Contribution is calculated by giving 50% credit to the last click and then dividing the remainder of the credit between Display and SEM proportional to the number of touchpoints prior to the last click; only SEM and Display qualify for indirect contribution credit based on data availability

Comparing the various contribution estimates suggests that while SEM is good for closing, Display helps to fill the pipeline

Channel [1]	Last Click	Fractional SEM	Fractional Display [1]	Fractional Other
Direct	1,323	164.3	219.7	939
Email	851	103.6	154.9	592.5
Organic Search	1,274	129.9	150.1	994
Other Nonpaid	341	35.9	24.1	281
Display	264	16.8	247.3	0
SEM	1,541	1,322.3	218.8	0
Total	**5,594**	**1,772.7**	**1,014.8**	**2,806.5**

1 – Each row corresponds to the channel in which the last click occurred such that the values in the fractional attribution columns correspond to the fractional credit given to SEM, Display and all other channels broken out by the channel in which the last click occurred; the intersection of the Channel row and the Fractional Other column is the fractional contribution estimate for that channel

Although SEM offers the best return, Display still merits continued spending

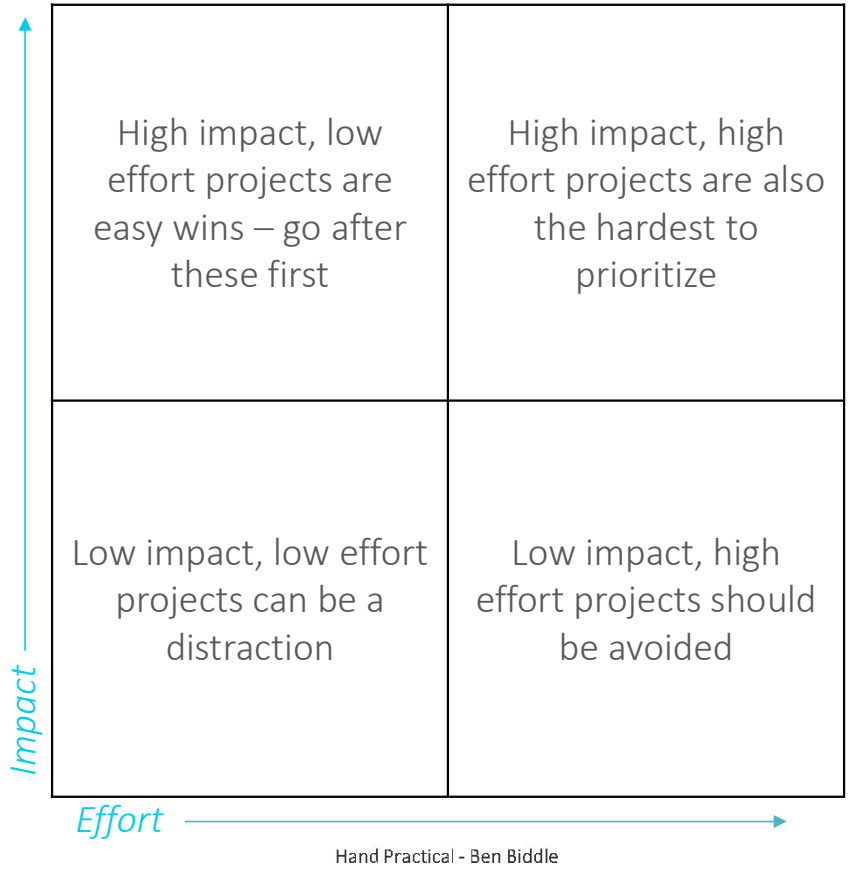
	SEM		Display	
Total Spending		$214,500		$136,600
	Last Click	Fractional	Last Click	Fractional
Attributed Revenue	$389,150	$450,648	$66,250	$257,962
Net Attributed Revenue	$174,650	$236,148	$(70,350)	$121,362
Estimated Return	81%	110%	-52%	89%

The negative return on Display spending, under last click attribution, suggests the best results might come from 1) running branding in Display and direct response in SEM and 2) potentially rebalancing the mix in favor of more SEM

Project Prioritization

How do we get the most value out of our Analytics resources?

To start, we should always prioritize work according to the expect impact and effort



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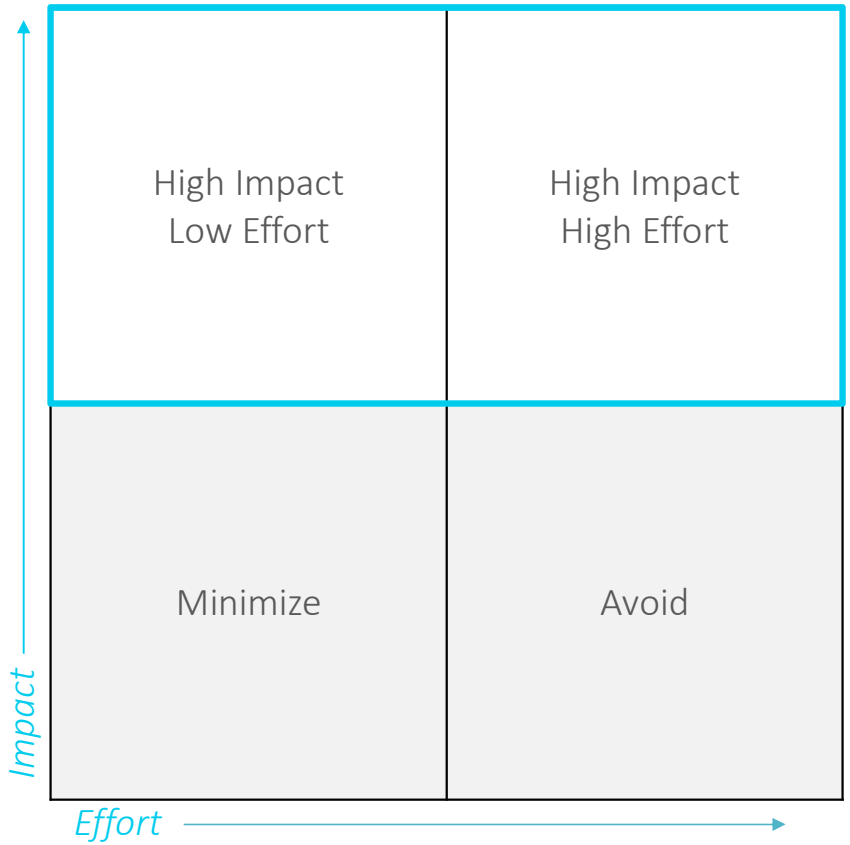
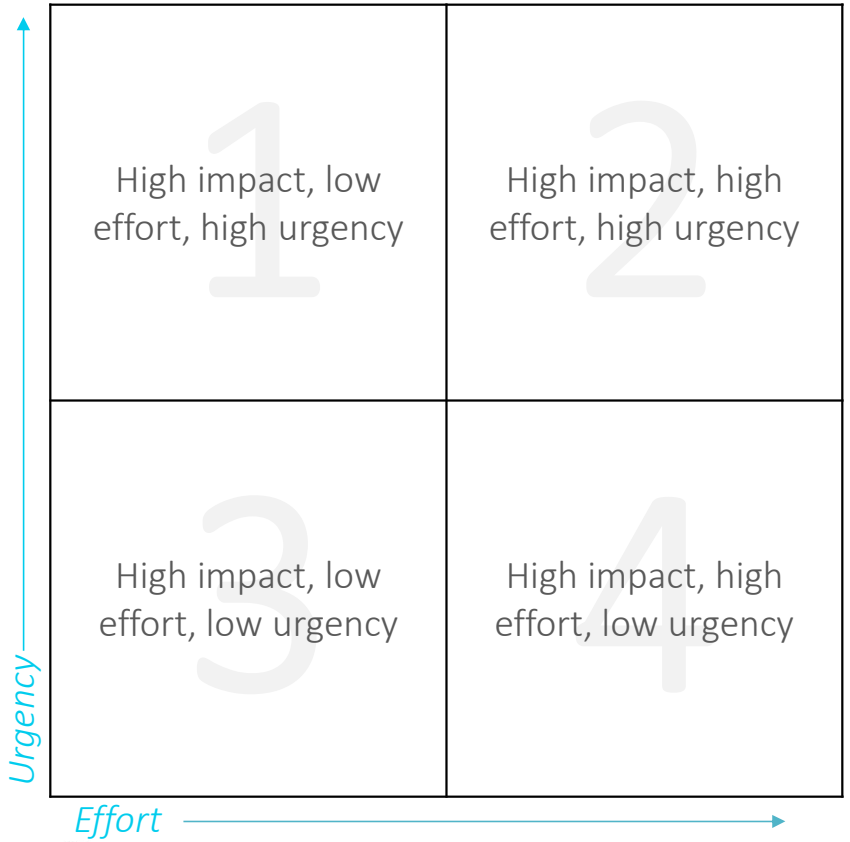
A second dimension – urgency – must also be considered to decide which high impact projects to prioritize first





In practice, estimating the impact, effort and urgency of projects can be challenging in and of itself

- Think of impact in terms of what will happen if the project never gets done rather than the expected benefits of doing the project
  - If the project never gets done, are there other suitable ways to meet the underlying need?
- The point in time after which those negative consequences can no longer be avoided determines the urgency
  - Sometimes the negative consequences will be a direct function of time elapsed; in such cases, pick a point in time in the future and base the impact and urgency off that timeframe
- Effort is most easily expressed in terms of the total hours required to deliver against the project requirements, which the Analytics team is best suited to estimate

As needs are identified, collect them into a backlog and work with stakeholders to rate the impact and urgency

Request	Impact	Urgency	Effort
Market Sizing	8	Low	20 hours
A|B Test	7	Low	10 hours
SEM Performance	9	Medium	15 hours
Pricing Analysis	6	Low	10 hours
New Partnership	9	High	40 hours
Churn Analysis	6	Low	15 hours

- Using an index to quantify impact, with guidelines for dollar equivalents, can be easier for stakeholders to work with
- Similarly, High/Medium/Low is typically sufficient for quantifying urgency – but still include a deadline for completing the work
- The Analytics team should fill in the estimated time required with the Head of Analytics making the final call

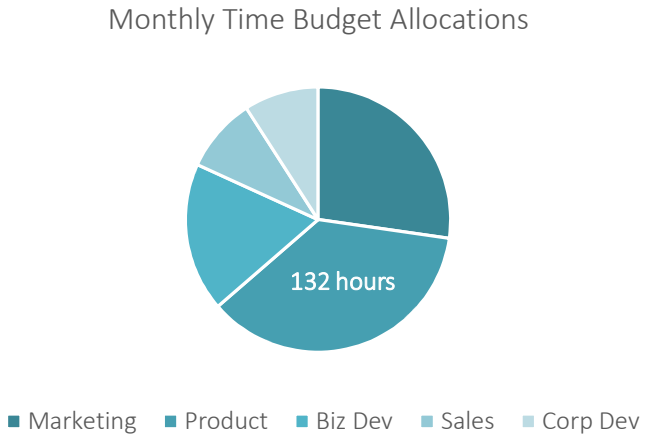
Periodically review the backlog and all work-in-progress to assess whether priorities need to be adjusted

Request	Impact	Urgency	Effort
Market Sizing	8	Low	20 hours
A|B Test	7	Low	10 hours
SEM Performance	9	Medium	15 hours
Pricing Analysis	6	Low	10 hours
New Partnership	9	High	40 hours
Churn Analysis	6	Low	15 hours

- Sometime needs will arise that require putting other work on hold
  - Work with the impacted stakeholders to come up with contingency plans
- Stakeholders may overstate the impact and/or urgency of a request to push their priorities up in the backlog
  - One effective way of mitigating such behavior is to agree upon a time budget for each group in advance

Because some groups will have more need for analytics than others, time budget allocations need not be the same for all

- Assume an analytics team of 3 people: 2 analysts and 1 manager
- Further assume that 80% of the analysts' time and 50% of the manager's are available for working on analytics projects
  - The remaining time is set aside for administrative overhead and other work
- Of the 364 available hours each month, each group would be allocated a portion based on the previously agreed upon intensity of need for that group
- Groups then spend their time budget on specific requests
  - Estimates of impact and urgency get baked into how groups decide to spend their budget
- If a group exhausts its budget for a given month, they can borrow from other groups against future months budget – *managing the trade-offs in a literal sense*
- Budgets should always be constrained; if a group's budget consistently exceeds its needs, some portion should be reallocated to other groups going forward



A final word on operating principles for the team

- Don’t let perfection be the enemy of the good
  - “Torture the data long enough and it will confess to anything.” – Ronald Coase
  - “All models are wrong but some are useful.” – George Box
- Avoid duplicative effort but ask for help when you need it
- Update stakeholders on progress at a regular cadence
  - Never wait to flag risks or potential delays
  - Always bring solutions to the table instead of just problems
- Good strategy requires focus
  - Deciding what not to do is often the most important decision to be made

Thanks!