Customer-based Corporate Valuation

Professor Daniel McCarthy

danielmc@wharton.upenn.edu

http://www.danielminhmccarthy.com

Professor Peter Fader

faderp@wharton.upenn.edu

Twitter: @faderp

ASA Seminar Series

July 24, 2017

The sources of corporate valuation

FIRM'S TOTAL EQUITY

OPERATING ASSETS
(sales ops, brand, technology, distribution, production, HR, …)

NON-OPERATING ASSETS
(excess real estate, other investments)

NET DEBT
(cash and equivalents, debt, lease obligations)

The sources of corporate valuation

- **FIRM'S TOTAL EQUITY**
  - **OPERATING ASSETS**
    (sales ops, brand, technology, distribution, production, HR, …)
    - **CUSTOMERS**
  - **NON-OPERATING ASSETS**
    (excess real estate, other investments)
  - **NET DEBT**
    (cash and equivalents, debt, lease obligations)

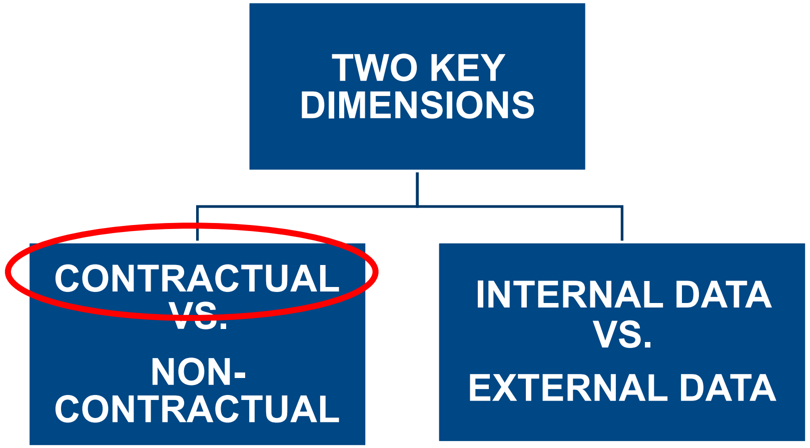
Customer-Based Corporate Valuation

TWO KEY DIMENSIONS

CONTRACTUAL
VS.
NON-CONTRACTUAL

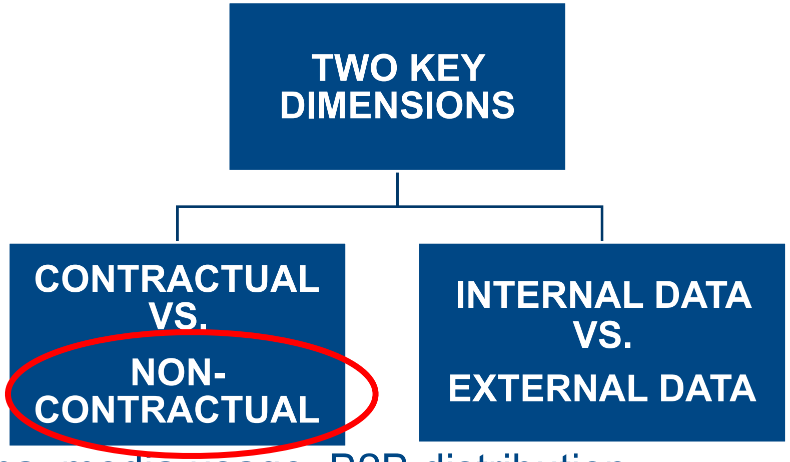
INTERNAL (GRANULAR) DATA
VS.
EXTERNAL (AGGREGATED) DATA

Contractual vs. Non-contractual



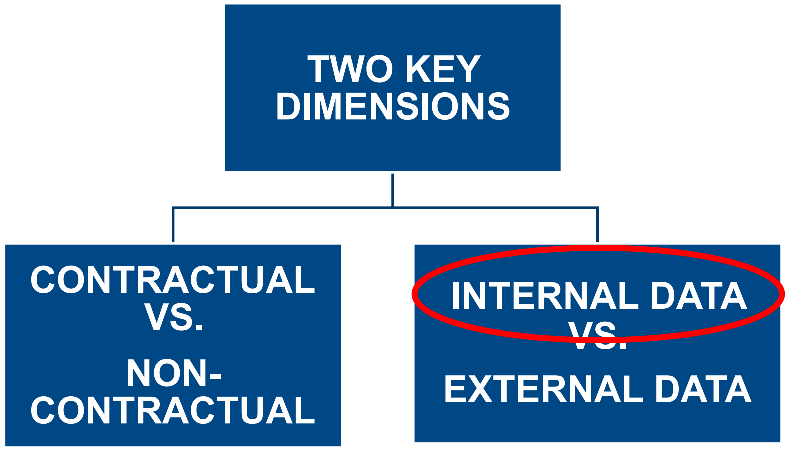
- **Contractual:**
  - Observable attrition
    - Telcos, insurance, club memberships, SaaS, etc.
  - Relatively steady payments over lifetime
  - Easy to model
  - But less common than non-contractual

Contractual vs. Non-contractual



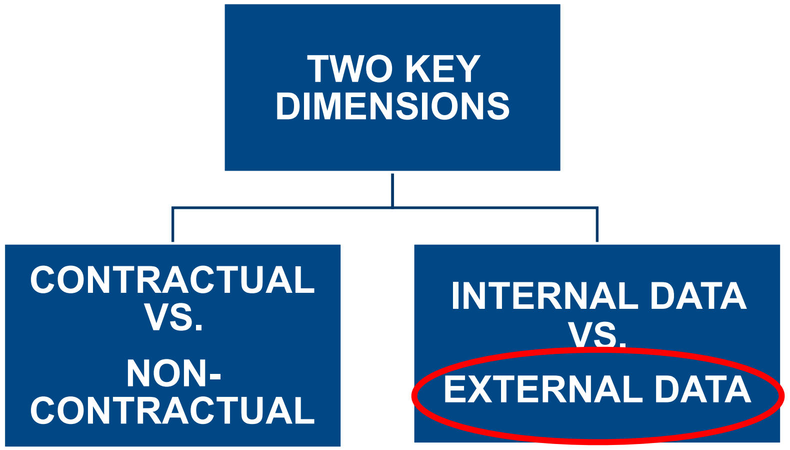
- **Non-contractual:**
  - Latent attrition
    - Retail, restaurants, gaming, travel, entertainment, healthcare/pharma, media usage, B2B distribution, …
  - Very “random” purchase timing and spend over lifetime
  - Much harder to model
    - Can’t approximate it as contractual
    - But suitable methods are now well-established

Internal vs. External Data



- **Internal (granular)**
  - Customer-level transaction logs
  - Can be augmented by other sources
    - Marketing action, satisfaction, social media

Internal vs. External Data



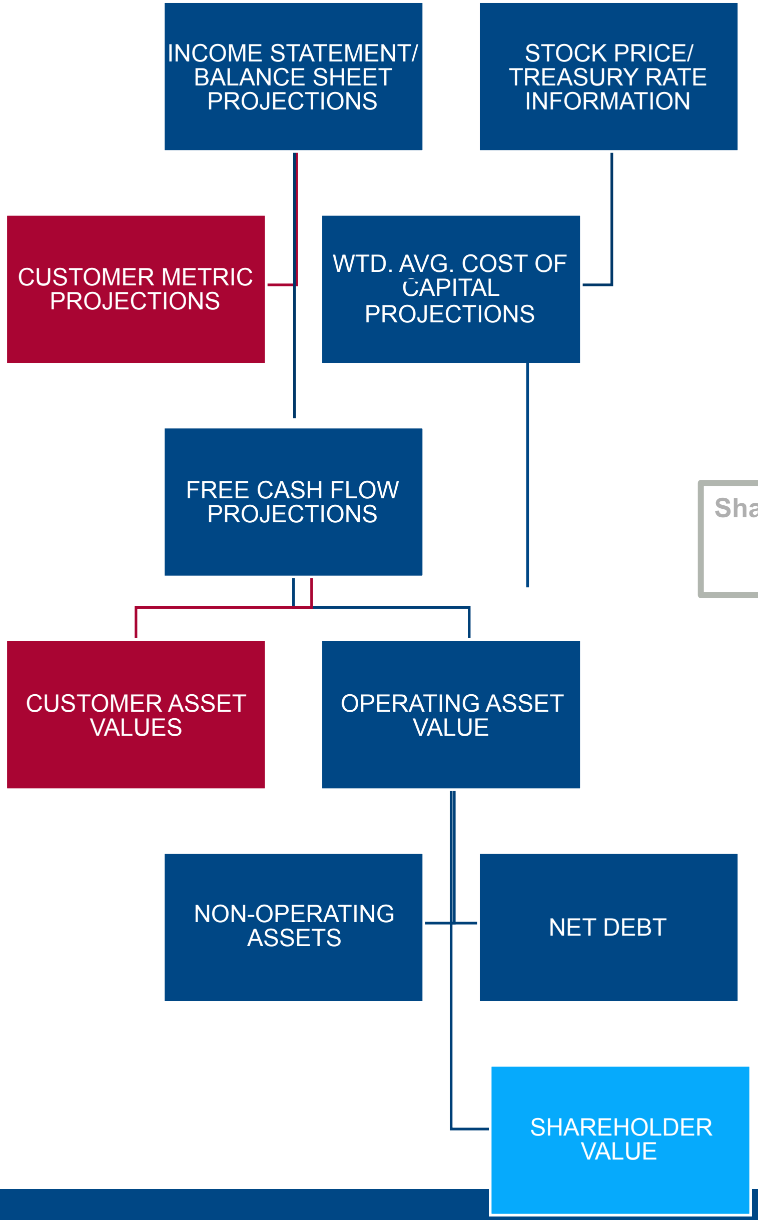
- **External (aggregated)**
  - “Rolled up” summaries
  - Periodically disclosed
    - First-party disclosures (10-K’s, 10-Q’s, investor presentations, etc.)
    - Third-party disclosures (Slice Intelligence, 1010data, SecondMeasure, etc.)

Discounted Cash Flow Valuation Model

Benefits:

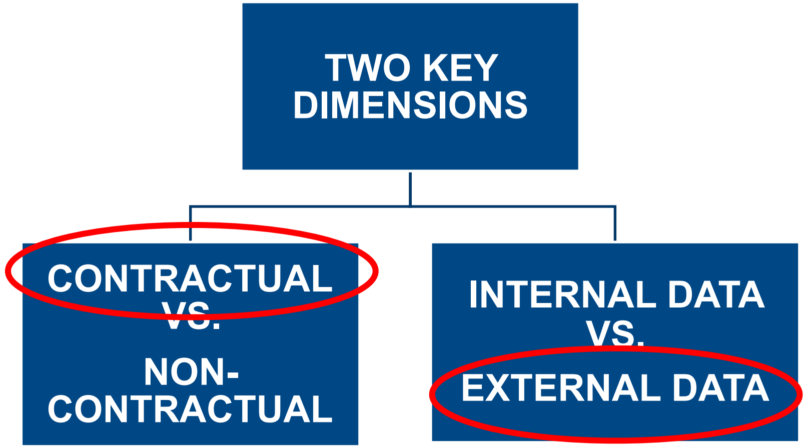
1. De-facto standard method (Koller/Goedhart/ Wessels 2010)
2. Flexible (changes in debt / working capital / operating expenses)
3. General (values whole enterprise)
4. Naturally integrates customer metric projections!

→ Asset/CE-based analyses are nested.



Shareholder Value = Operating Asset Value
+ Non-Operating Assets
– Net Debt

Case Study #1: DISH Network



- Contractual company
- External/aggregate data
- Compare to market valuation as well as Wall Street analyst revenue forecasts

Paper available at http://whr.tn/CorpValPaper1

Dish Network Data

Period	Adds	Losses	Ending
Q1 1996	0	0	0
Q2 1996	NA	NA	100
Q3 1996	NA	NA	190
Q4 1996	NA	NA	350
Q1 1997	NA	NA	479
Q2 1997	NA	NA	590
Q3 1997	NA	NA	820
Q4 1997	NA	NA	1040
Q1 1998	204	44	1200
Q2 1998	236	36	1400
Q3 1998	267	67	1600
Q4 1998	395	55	1940
Q1 1999	400	40	2300
Q2 1999	414	114	2600
Q3 1999	500	100	3000
Q4 1999	580	170	3410
Q1 2000	585	95	3900
Q2 2000	618	218	4300
Q3 2000	648	148	4800
Q4 2000	705	245	5260
Q1 2001	688	248	5700
Q2 2001	656	286	6070
Q3 2001	684	324	6430
Q4 2001	692	292	6830
Q1 2002	619	289	7160
Q2 2002	642	342	7460

Period	Adds	Losses	Ending
Q3 2002	722	402	7780
Q4 2002	804	404	8180
Q1 2003	687	337	8530
Q2 2003	701	431	8800
Q3 2003	746	461	9085
Q4 2003	759	419	9425
Q1 2004	785	425	9785
Q2 2004	851	511	10125
Q3 2004	897	547	10475
Q4 2004	907	477	10905
Q1 2005	801	476	11230
Q2 2005	799	574	11455
Q3 2005	900	645	11710
Q4 2005	897	567	12040
Q1 2006	794	569	12265
Q2 2006	824	629	12460
Q3 2006	958	663	12755
Q4 2006	940	590	13105
Q1 2007	890	580	13415
Q2 2007	850	680	13585
Q3 2007	904	794	13695
Q4 2007	790	705	13780
Q1 2008	730	695	13815
Q2 2008	752	777	13790

Period	Adds	Losses	Ending
Q3 2008	825	835	13780
Q4 2008	659	761	13678
Q1 2009	653	747	13584
Q2 2009	731	705	13610
Q3 2009	887	646	13851
Q4 2009	847	598	14100
Q1 2010	833	596	14337
Q2 2010	747	766	14318
Q3 2010	819	848	14289
Q4 2010	653	809	14133
Q1 2011	681	623	14191
Q2 2011	572	707	14056
Q3 2011	656	767	13945
Q4 2011	667	645	13967
Q1 2012	673	569	14071
Q2 2012	665	675	14061
Q3 2012	739	758	14042
Q4 2012	662	648	14056
Q1 2013	654	618	14092
Q2 2013	624	702	14014
Q3 2013	734	699	14049
Q4 2013	654	646	14057
Q1 2014	639	599	14097
Q2 2014	656	700	14053
Q3 2014	691	703	14041
Q4 2014	615	678	13978
Q1 2015	554	688	13844

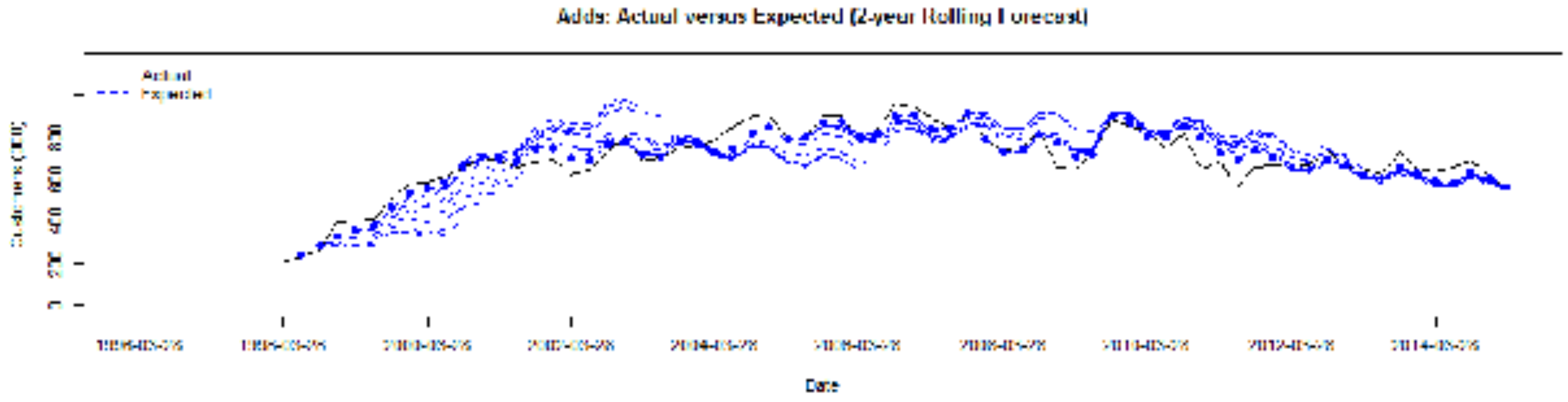
Valuing Contractual Firms: "Customer Triangle"

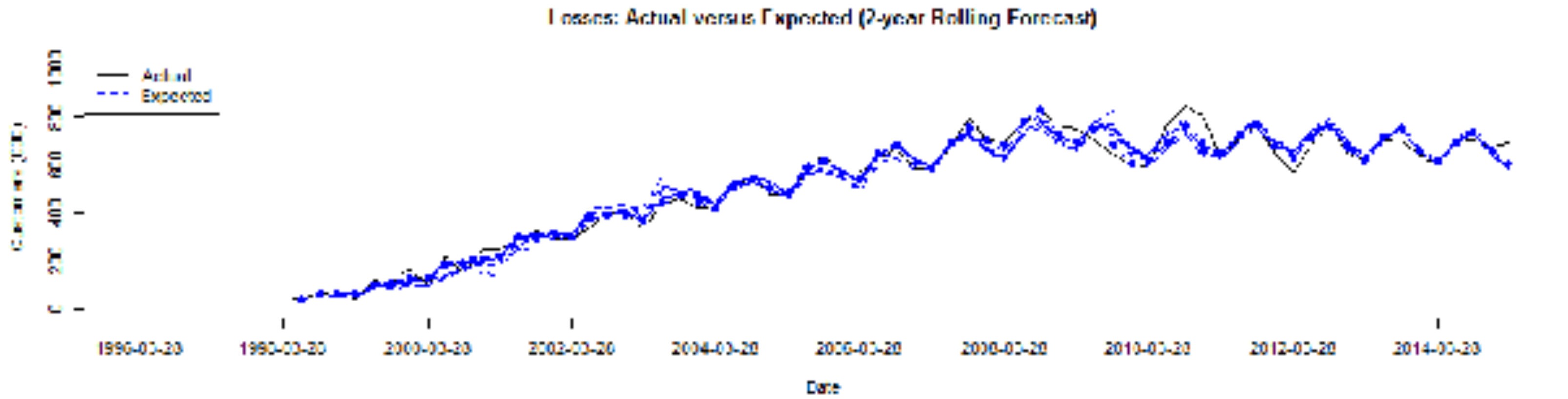
	Active Customers by Cohort								
Month	**1**	**2**	**3**	**4**	**5**	**6**	**Total Customers**	**x ARPU**	**= Revenue**
Jan-16	1.06						1.06	50.00	53
Feb-16	1.04	1.29					2.33	50.15	117
Mar-16	1.02	1.26	1.43				3.71	50.30	187
Apr-16	1.00	1.24	1.40	1.47			5.11	50.45	258
May-16	0.98	1.21	1.37	1.44	1.84		6.85	50.60	346
Jun-16	0.96	1.19	1.35	1.41	1.80	2.09	8.80	50.75	447

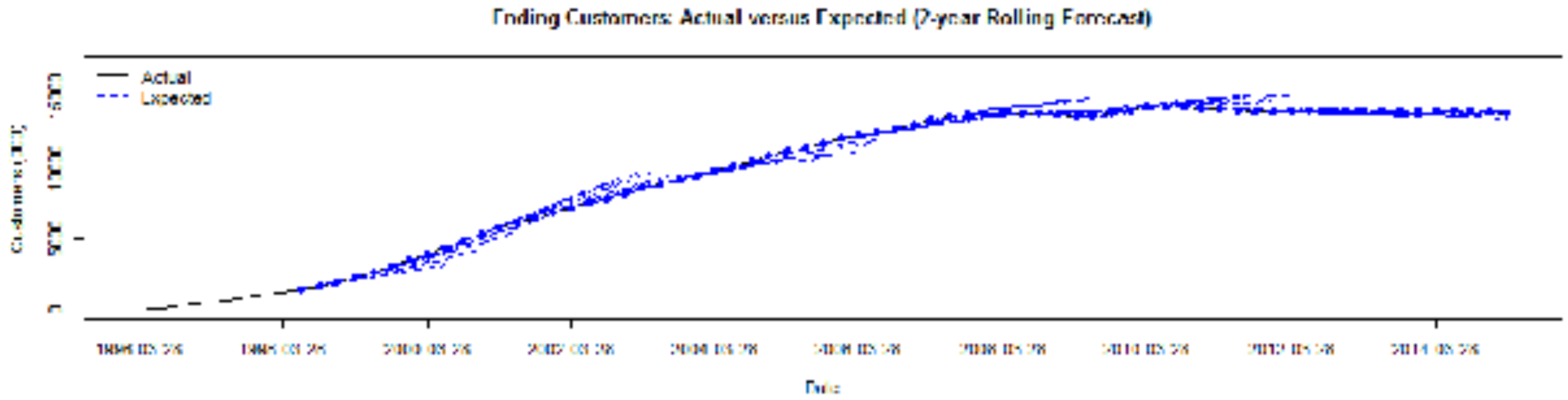
Attrition **Acquisition** **Total Customers** **Spend**

Estimated off of quarterly marginal acquisition/loss data

Wharton


Adds: Actual versus Expected (2-year Rolling Forecast)
Actual
Expected
Date


Losses: Actual versus Expected (2-year Rolling Forecast)
Actual
Expected
Date


Ending Customers: Actual versus Expected (2-year Rolling Forecast)
Actual
Expected
Date

Valuation Results

Table 4: Dish Valuation Summary (End of Q1 2015)

Value of Operating Assets	\$15.7B
Non-Operating Assets - Net Debt	\$14.1B
Shareholder Value	\$29.9B
Shares Outstanding	462.1MM
Implied Stock Price	\$64.62
Actual Stock Price	\$66.38
Over(under)-estimation	(2.7%)

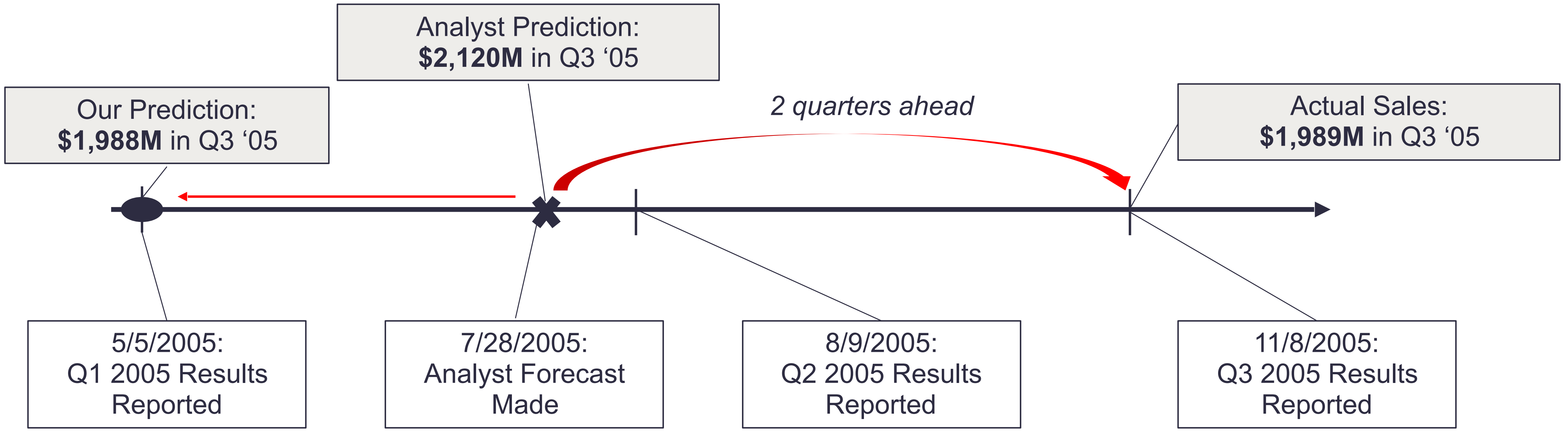
McCarthy, Fader, Hardie (2017), "Valuing Subscription-Based Businesses Using Publicly Disclosed Customer Data," *Journal of Marketing, 81(1), 17-35.*

Validation vs Wall Street Analyst Projections

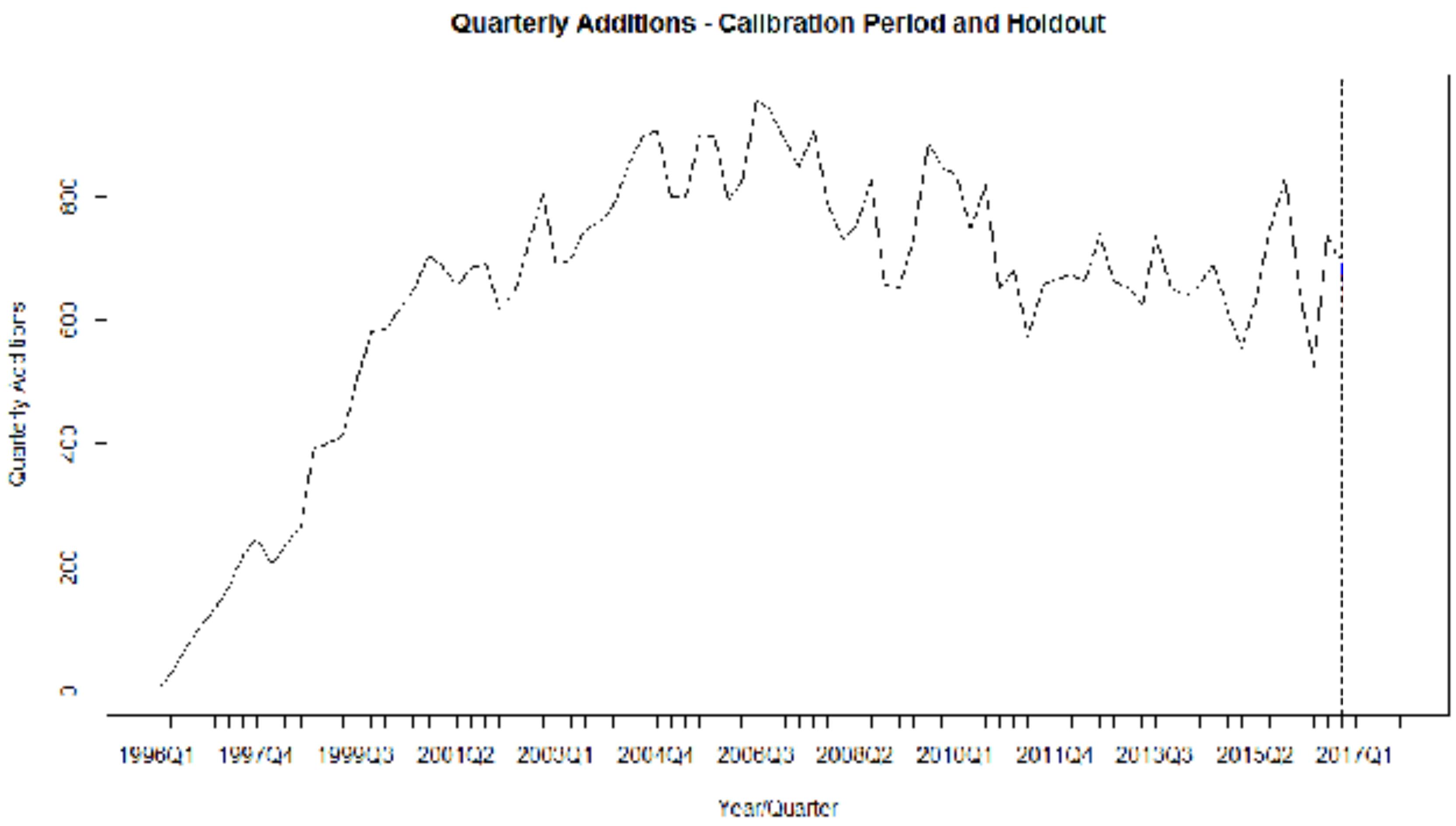
- 3,454 quarterly sales predictions by analysts
  - Predictions made 5/2001 - 12/2014
  - Varying time horizons
- → How does our predictive accuracy compare?

Our forecasts are consistently 10-15% more accurate than those of the Wall Street analysts

Example:

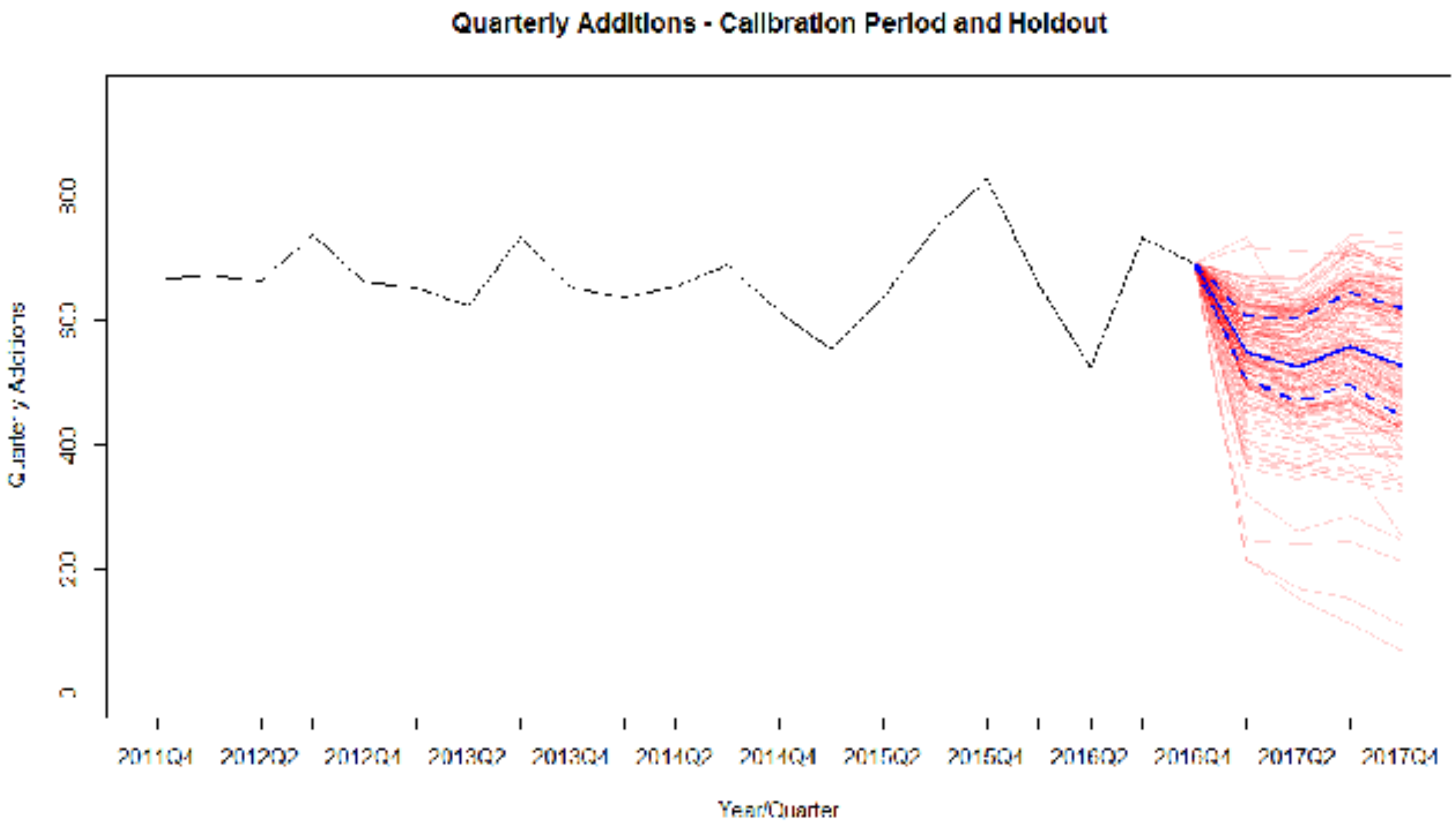


An update…



Wharton

An update…



Quarterly Additions - Calibration Period and Holdout
Quarterly Additions
2011Q4
2012Q2
2012Q4
2013Q2
2013Q4
2014Q2
2014Q4
2015Q2
2015Q4
2016Q2
2016Q4
2017Q2
2017Q4
Year/Quarter

MarketWatch

http://on.mktw.net/2qB1FPt

Opinion: How Wharton marketing students beat Wall Street analysts at their own game

By Dan McCarthy and Peter Fader

Published: May 30, 2017 12:46 p.m. ET

Consider Dish Network DISH, +1.64% the U.S. satellite-television provider. On May 1, Dish reported in its first-quarter earnings release that it had acquired 547,000 new customers. Wall Street was disappointed — this metric came in below analysts' expectations, which contributed to net customers acquired and overall revenues trailing Wall Street's estimates. Dish's stock price fell that day and by the end of the week was down 4.4%, erasing $1.3 billion in shareholder value.

Wall Street analysts did not see it coming. Sell-side analysts' forecast for gross adds as of April 12 (available through Thomson One) over-predicted by more than 13%.

Was anyone *not* caught by surprise? Yes, the students in our marketing course, "Applied Probability Models in Marketing." Every year, we here at Wharton assign a project in which students apply the statistical models they have learned in the class to a real-world problem. This year, we tasked them to predict new customer acquisitions for Dish.

Accurate prediction

On April 5, almost a month before first-quarter results were released, every student submitted his best guess of gross adds for the first to fourth quarters of 2017. In light of Dish's recent earnings release, the results are striking: a simple average of all 156 students' first-quarter predictions is 550,000, a mere 0.5% from the actual additions. In other words, the marketing students trounced the Street. Those students have not spoken with company management, listened to company guidance, analyzed competing firms or studied historical financials. They simply came up with the best statistical models they could for gross adds, stress-tested those models on Dish's historical data, then projected their models' output for 2017.

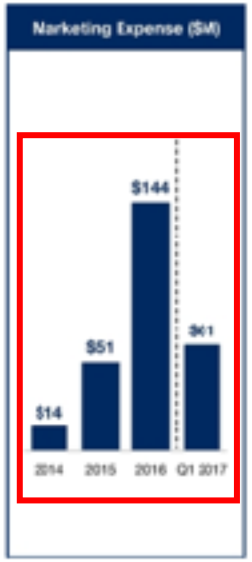
Case Study #2: Blue Apron

June 1st: Files S-1 for upcoming IPO

Not disclosed: Any churn metrics!

Disclosed:

	Three Months Ended				
	March 31, 2016	June 30, 2016	September 30, 2016	December 31, 2016	March 31, 2017
Orders (in thousands)	2,903	3,399	3,597	3,674	4,273
Customers (in thousands)	849	768	907	879	1,036
Average Order Value	$ 59.28	$ 59.40	$ 57.12	$ 58.78	$ 57.23
Orders per Customer	4.5	4.4	4.0	4.2	4.1
Average Revenue per Customer	$ 265	$ 264	$ 227	$ 248	$ 238
Net revenue *(in thousands)*	$ 172,098	$ 201,924	$ 205,452	$ 215,942	$ 244,843
Adjusted EBITDA *(in thousands)*	$ 5,048	$ 7,976	$ (34,627)	$ (22,018)	$ (46,265)

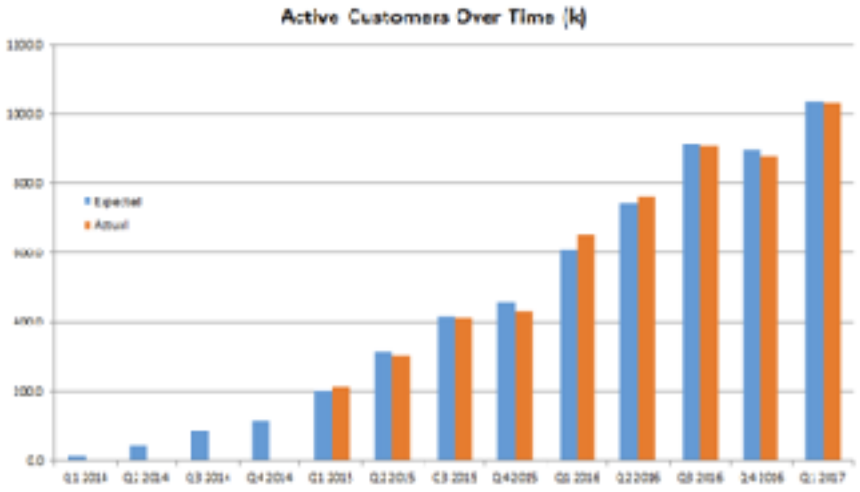


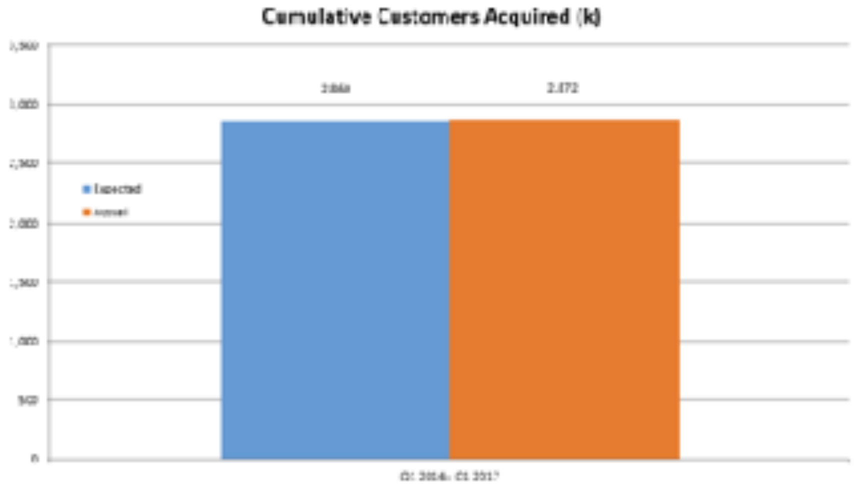
I fit the same model:

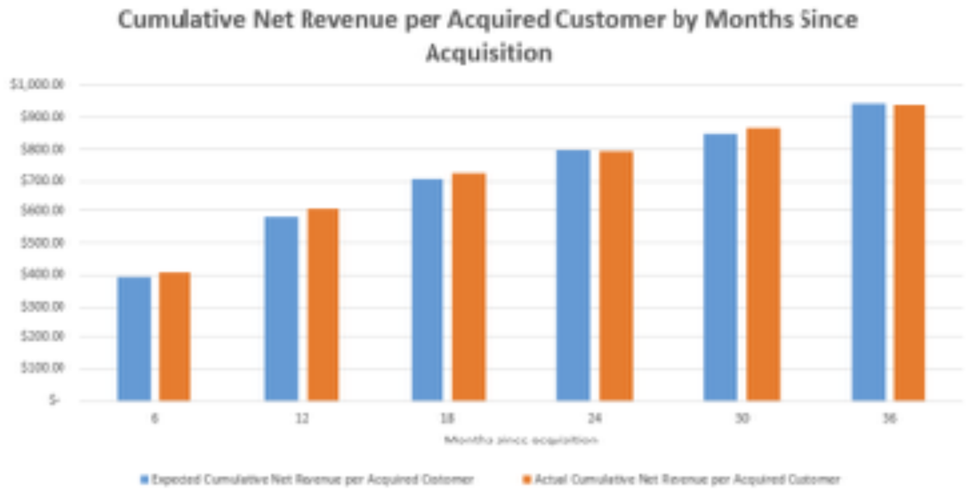
http://goo.gl/HZMpwx

http://goo.gl/s35Eg4

Model Validation

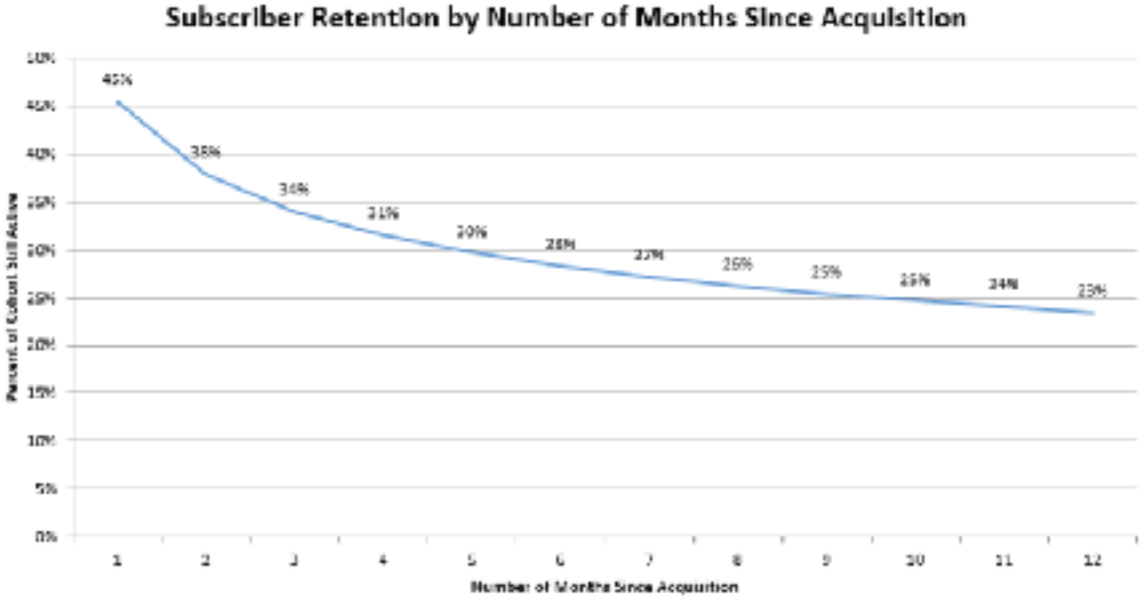




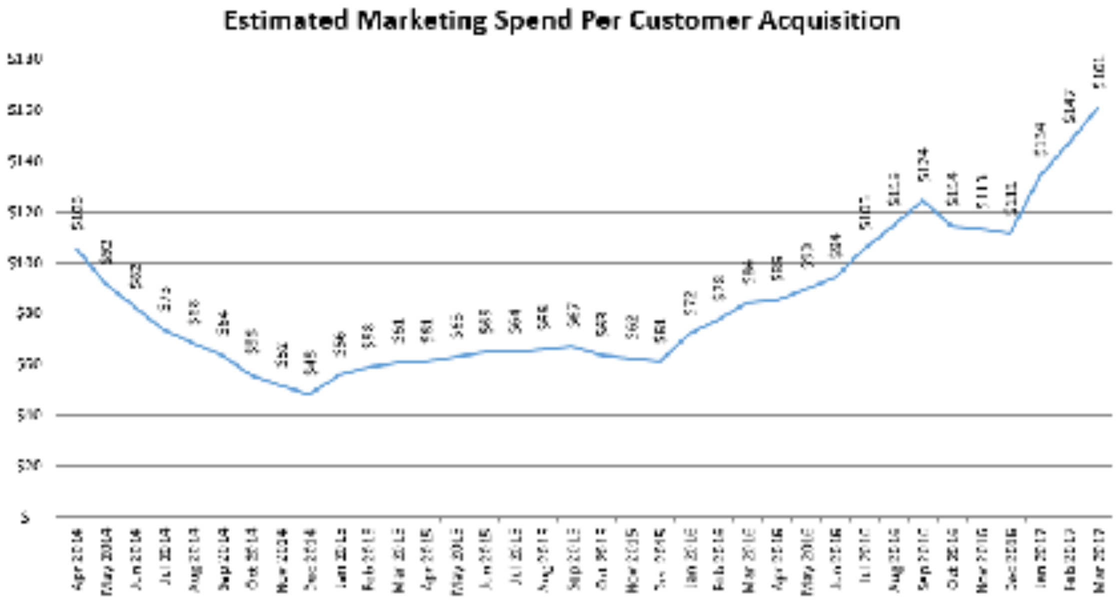


Model Insights

Challenging retention:



Rising CAC:



Media Reaction

THE WALL STREET JOURNAL.

TECH

Stir Fry on Sale? Blue Apron Turns to Deals to Draw Customers

Another problem is that Blue Apron appears to be churning through customers. The company doesn't disclose specifics, data in its securities filings about marketing spending and customer growth. But Daniel McCarthy, a professor of marketing at Emory University who has analyzed Blue Apron's numbers, estimated that at least 60% of customers stop using the service after six months.

"The retention at Blue Apron seems particularly troubling—very much out of the norm," Mr. McCarthy said, adding a more reasonable drop rate would be 30% to 40% after six months. "It becomes hard to see how they're going to grow their way into profitability."

FORTUNE | Finance

TERM SHEET

Term Sheet — Thursday, June 29

Erin Griffith
Jun 29, 2017

IPO: Blue Apron goes public today. The company priced at the bottom of its already-slashed range last night, bringing its valuation to $1.9 billion (wince). More details below, but I want to point to this analysis of the company's churn rate. Finding how quickly customers stop out of using Blue Apron was the first stat I looked for when the company filed its S-1, and I was disappointed when I realized the company didn't disclose it. Seems like an important stat to share with potential investors, but alas.

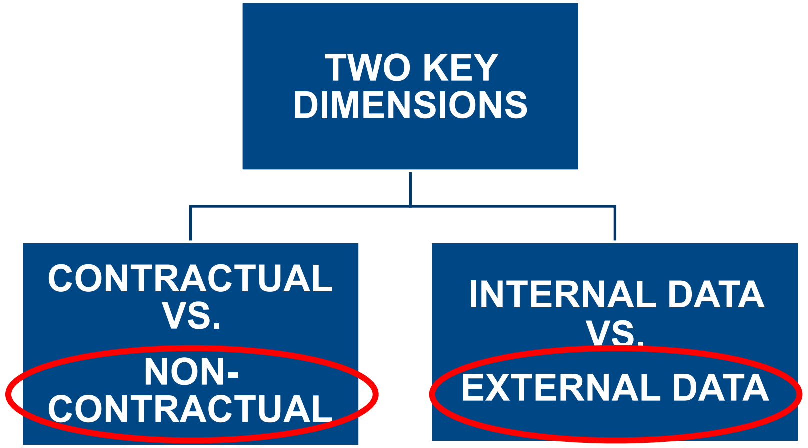
Daniel McCarthy, a professor and entrepreneur, has crunched some numbers using a retention curve technique he developed to arrive at this figure: 62% of Blue Apron customers churn within six months. Combine that with another stat that Blue Apron did disclose: It pays an average of $94 to acquire a customer. So: Blue Apron ended the first quarter with one million subscribers. That means, to merely stay flat, by my calculations, Blue Apron must pay $58 million every six months to *just replace the customers that leave*. To grow, it's gotta spend even more.

BUSINESS INSIDER BARRON'S The Motley Fool CBS Slate TheStreet.com RetailWire ad

Market Reaction

- Original IPO Range (6/19): $15-17
- Revised IPO Range (6/28): $10-11
- Actual IPO Price (6/29): $10
- Current Price (7/24): $7.41 (-26%)

Case Study #3: E-Commerce Retailer

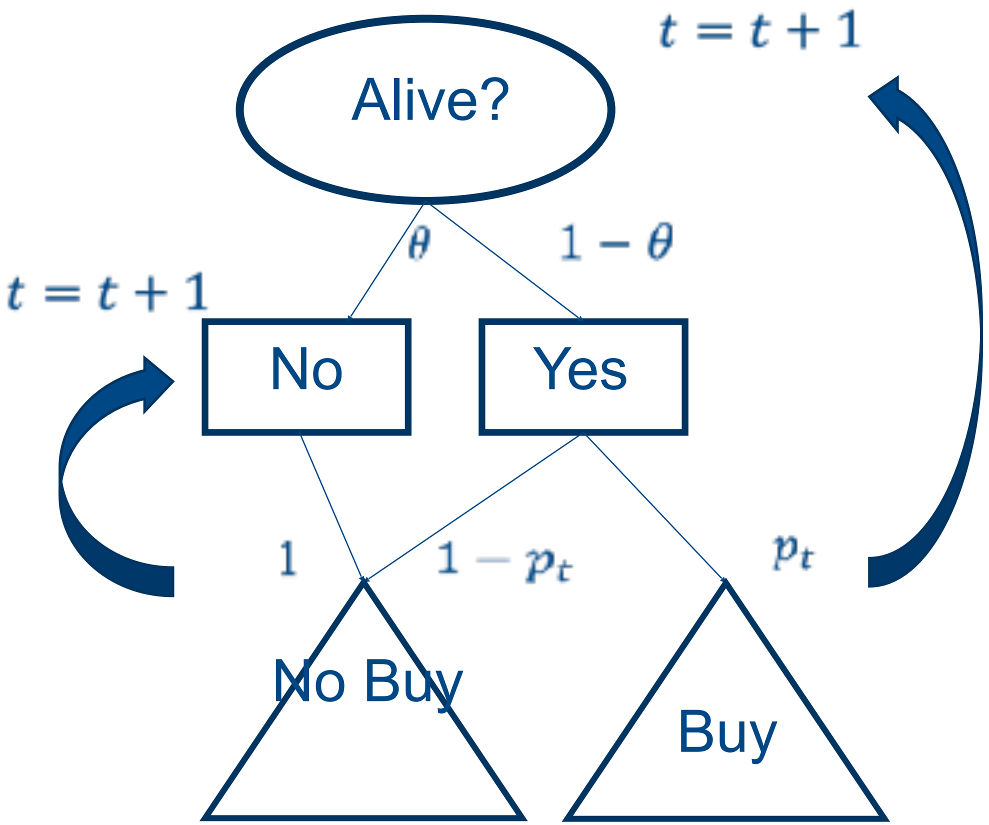


- Non-contractual company
  - Analysis for a single geographic region
- External/aggregated data
- Acquisition models virtually identical to contractual case
  - But how do we capture subsequent repeat purchasing and spend?
- Focus on choice of aggregated metrics

Paper available at http://whr.tn/CorpValPaper2

Repeat Purchase Process

Individual-Level



Across Population

$$\theta \sim Beta(\gamma, \delta)$$

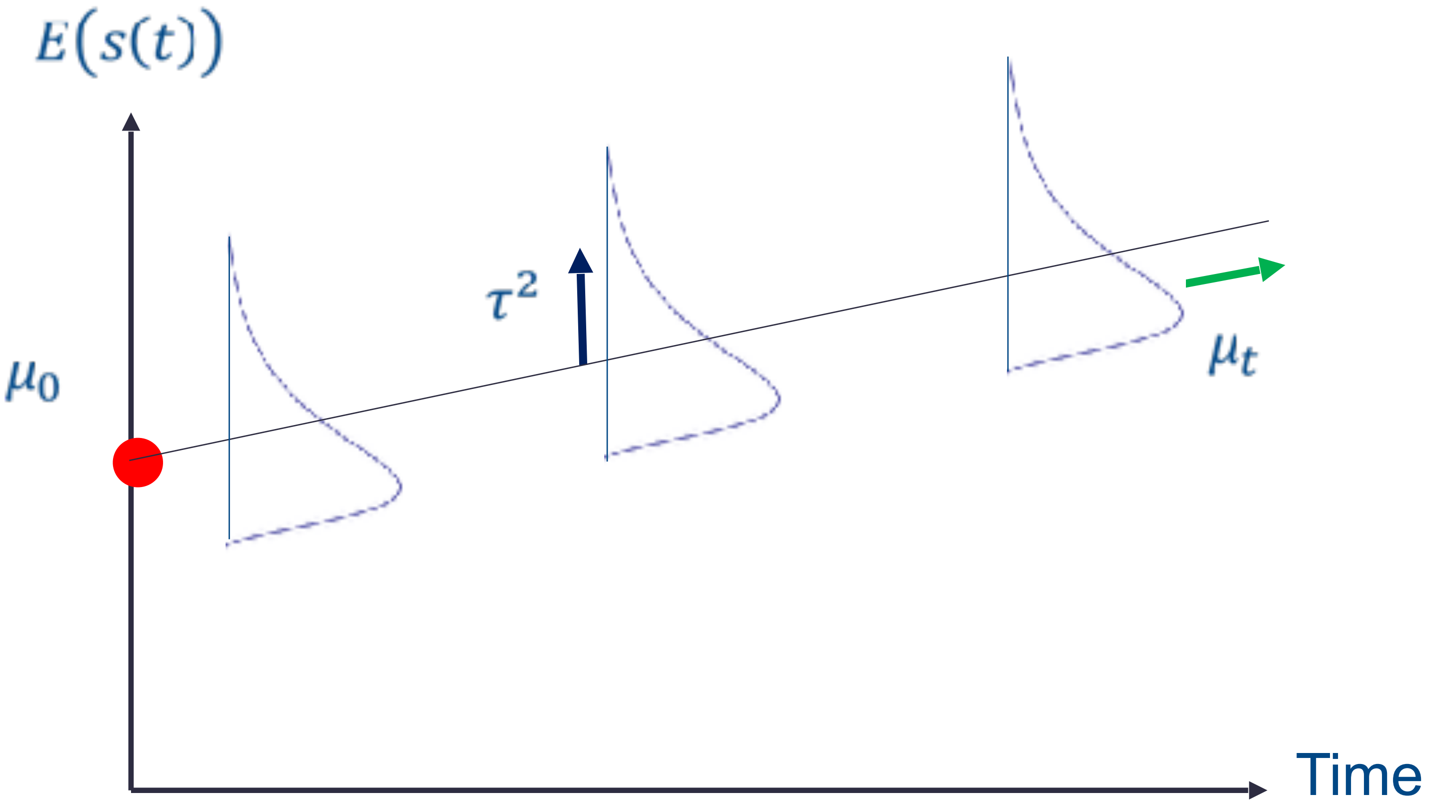
$$logit\, p_t = b_p + \boldsymbol{x}_p^T(t)\boldsymbol{\beta}_p$$
$$b_p \sim N(\mu_p, \sigma_p^2)$$

For seasonality / macroeconomy

Fader et al 2010

Spend Process

Expected spend per purchase for customers is lognormally distributed with drift:



Which *Spend* Metric Should Investors Want to See?

- Average spend per purchase we get “for free” from revenues, purchase process
- **Median spend per purchase** is excellent “companion metric” to average spend
  - Communicable to non-technical audiences
  - Natural measure of basket size
  - Mean and median over time strongly identify the spend process

Which *Purchase* Metrics Should Investors Want to See?

- Consider six metrics (from SEC filings) that reflect repeat-purchase patterns:
  - **AU: Active users** (# of customers who made > 0 purchases this year)
  - **HAU: Heavy active users** (# who made > 1 purchases this year)
  - **RR: Repeat rate** (% of last year's buyers who buy again this year)
  - **RBPO: Repeat buyer proportion-orders** (% of this year's orders from customers who bought previously)
  - **RBPC: Repeat buyer proportion-customers** (% of this year's buyers who bought who bought previously)
  - **F: Average frequency** (average purchases among active users)

Illustration

of Transactions by Year and Customer

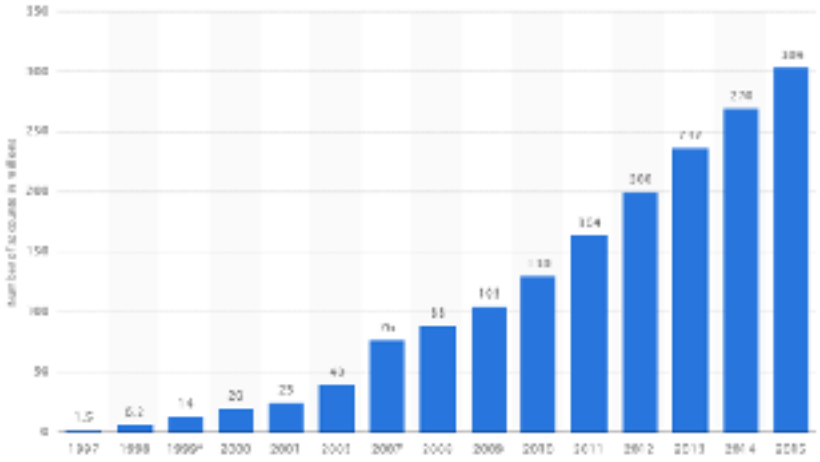
Customer	Y1	Y2	Y3
1	1	1	0
2		3	3
3			1
Gross adds	1	1	1
AU	1	2	2
HAU	0	1	1
RR	NA	100%	50%
RBPO	0%	25%	75%
RBPC	0%	50%	50%
F	1	2	2

Customer Metrics in Practice

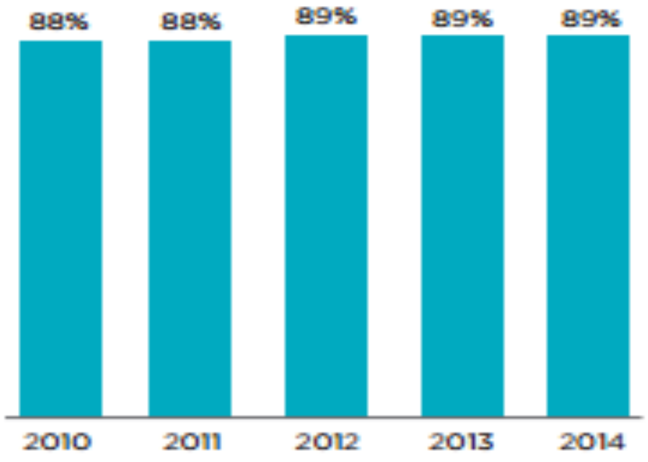
Active Users	QVC	evine LIVE	wayfair.com	amazon	
	CAMPING WORLD	GoPro	f	HSN	
Heavy Active Users	QVC	ULTA BEAUTY	AVEDA		
Repeat Rate	QVC				
Repeat Buyer Proportion	QVC	wayfair.com	amazon	HSN	jet
Frequency	evine LIVE				

Examples of Customer Metrics in Practice

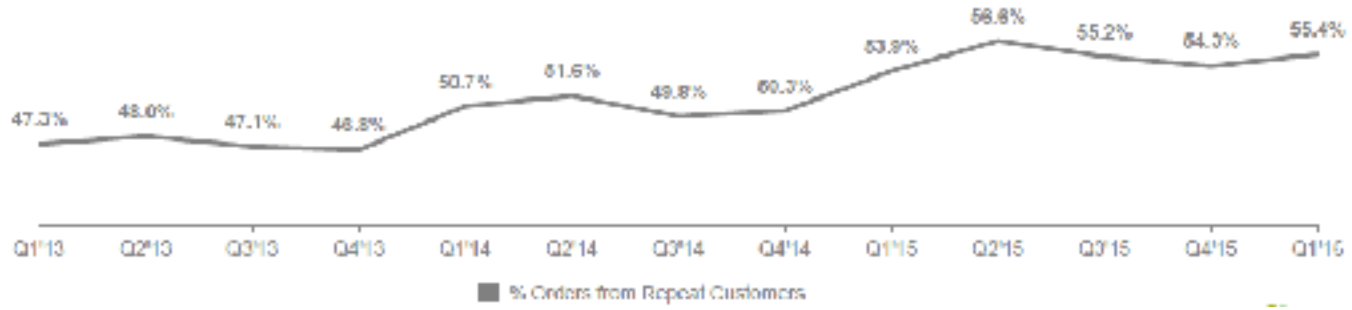
Amazon: Active Customers



QVC: Repeat Rate



Wayfair: Repeat Buyer Proportion



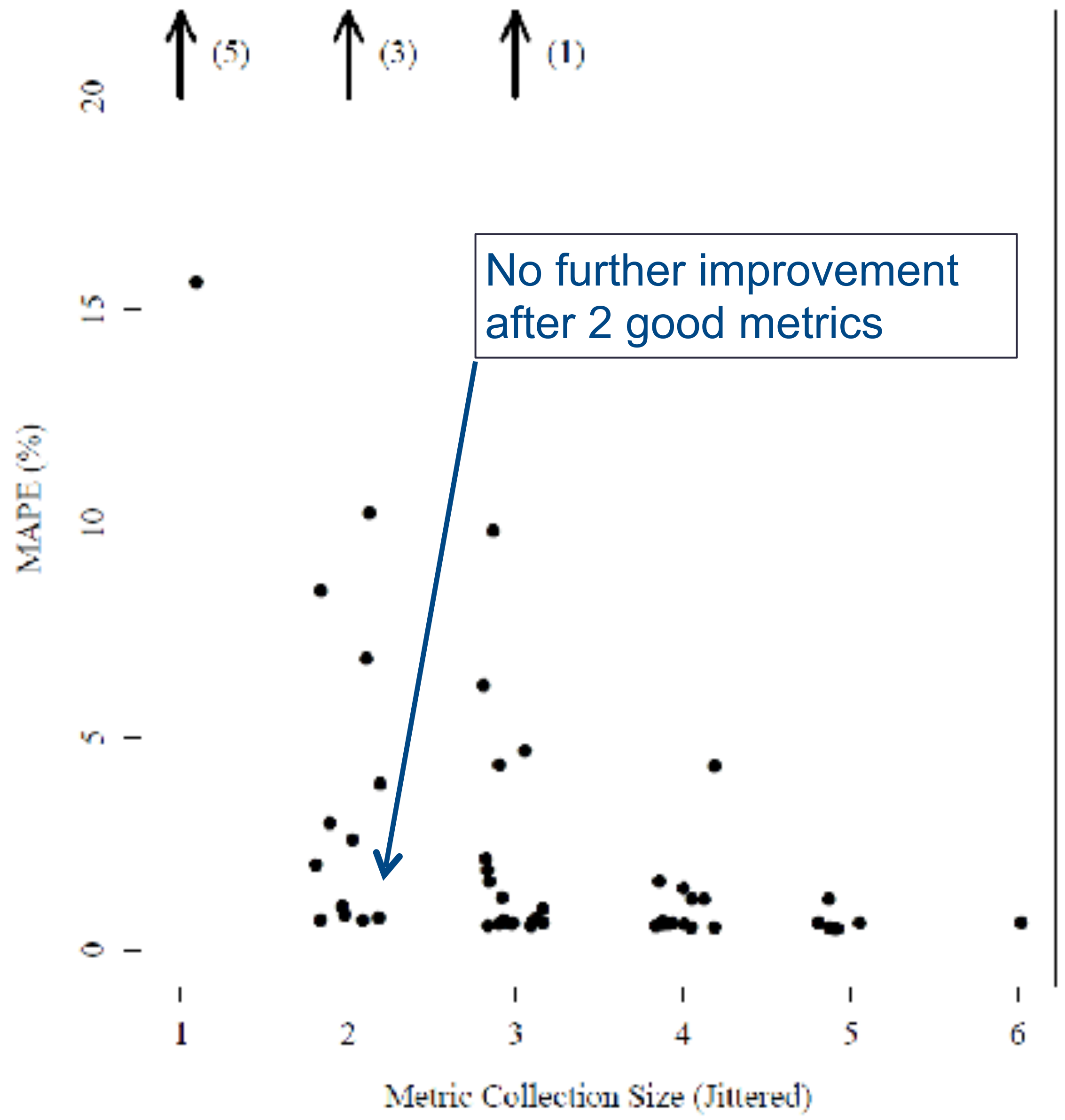
Which *Purchase* Metrics Should Investors Want to See?

- Consider six metrics (from SEC filings) that reflect repeat-purchase patterns:
  - **AU: Active users** (# of customers who made > 0 purchases this year)
  - **HAU: Heavy active users** (# who made > 1 purchases this year)
  - **RR: Repeat rate** (% of last year's buyers who buy again this year)
  - **RBPO: Repeat buyer proportion** (% of this year's orders from customers who bought before then)
  - **RBPC: Repeat buyer proportion** (% of this quarter's buyers who bought who bought before then)
  - **F: Average frequency** (average purchases among active users)

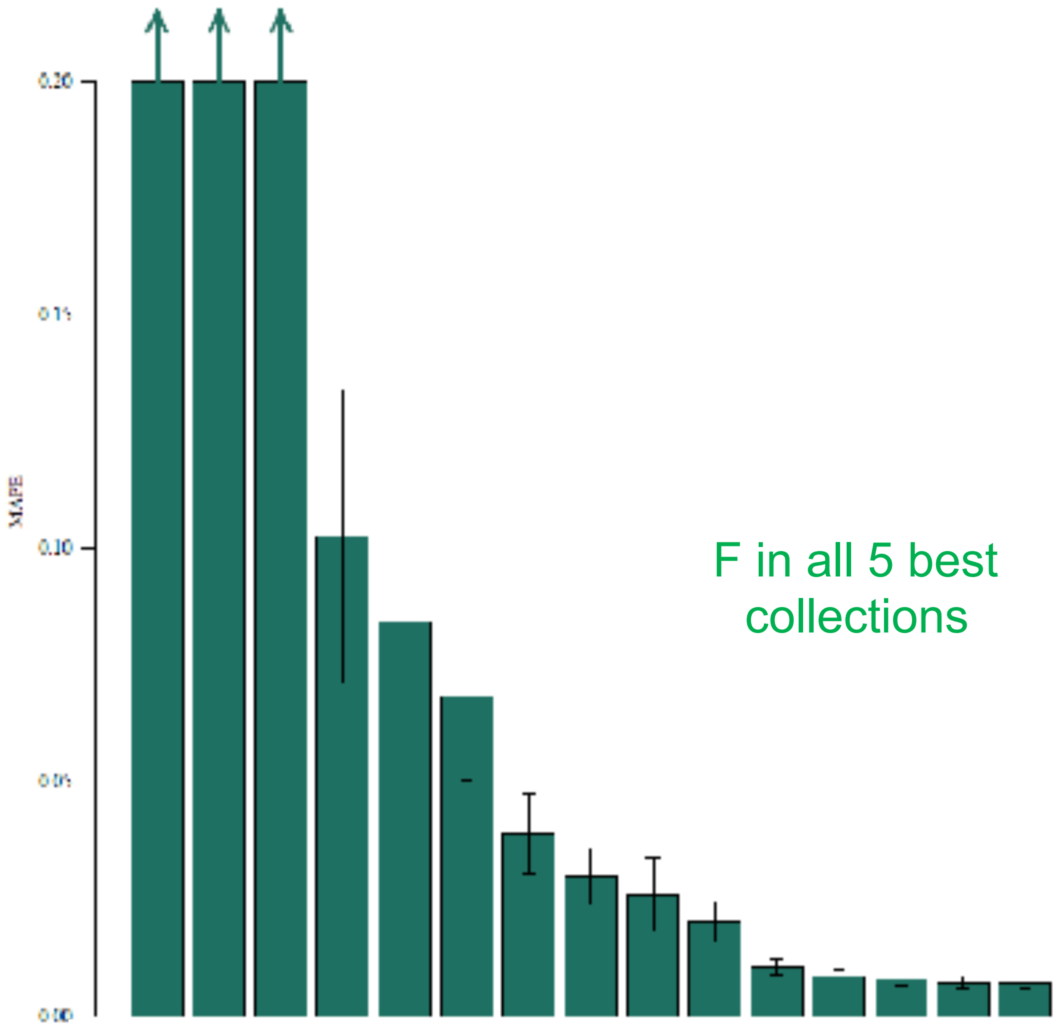
- How many metrics do investors need?
- Which metrics should investors demand?

→ We perform a large-scale simulation to answer these questions

Results: Average Error by Size (MAPE, count >20%)



Results: Average Error (MAPE), All Pairs



F in all 5 best collections

Valuation Example: E-commerce Retailer

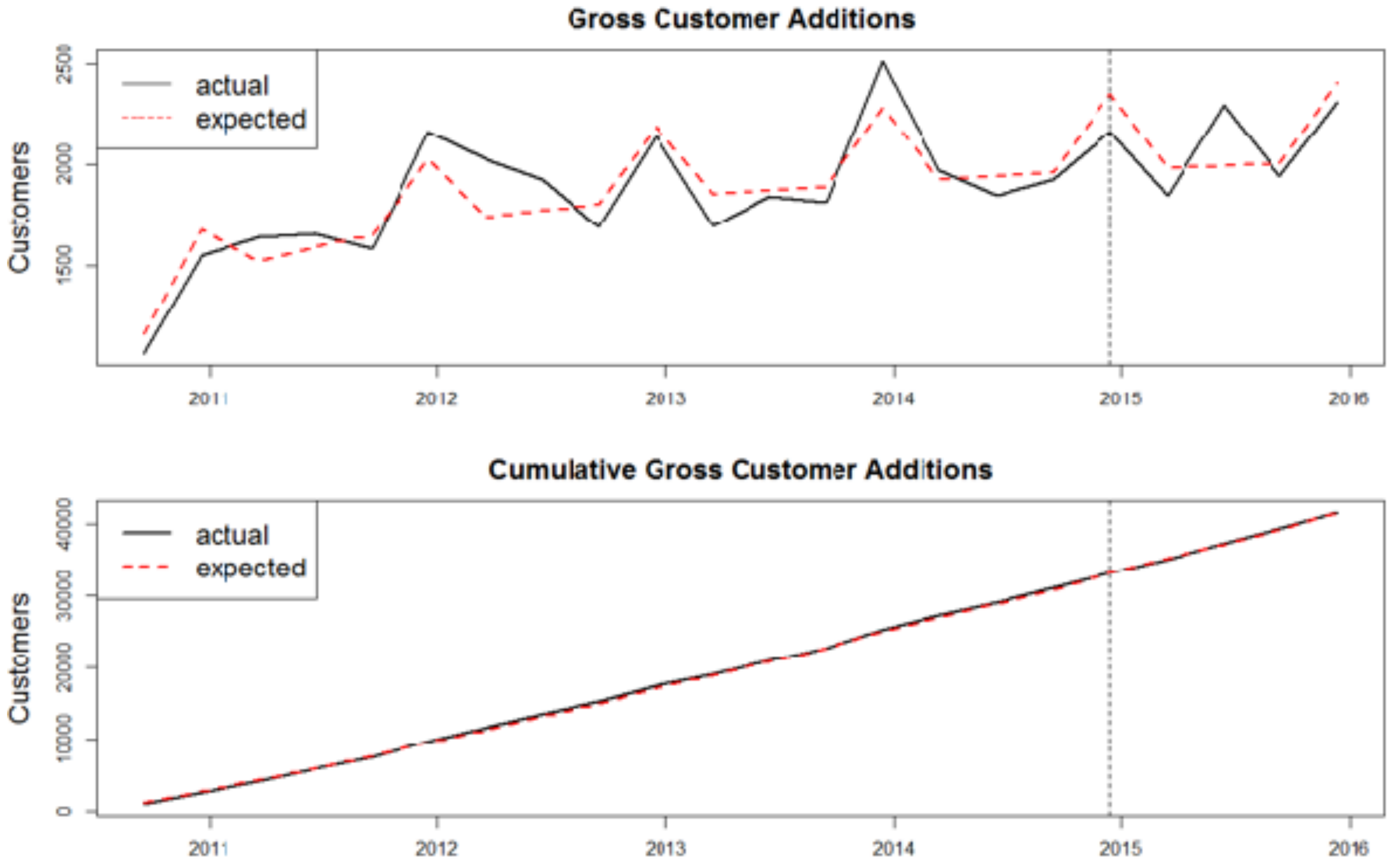
Consider a large business unit of an e-tailer:

- Commercial operations began July 1st 2010
- Track all purchases over subsequent 5.5 years
- For testing, split the 5.5 years (22 quarters) into two periods:
  - Estimate model on quarters 1-18 (“calibration period”)
  - Predict what will happen in quarters 19-22 (“holdout period”)

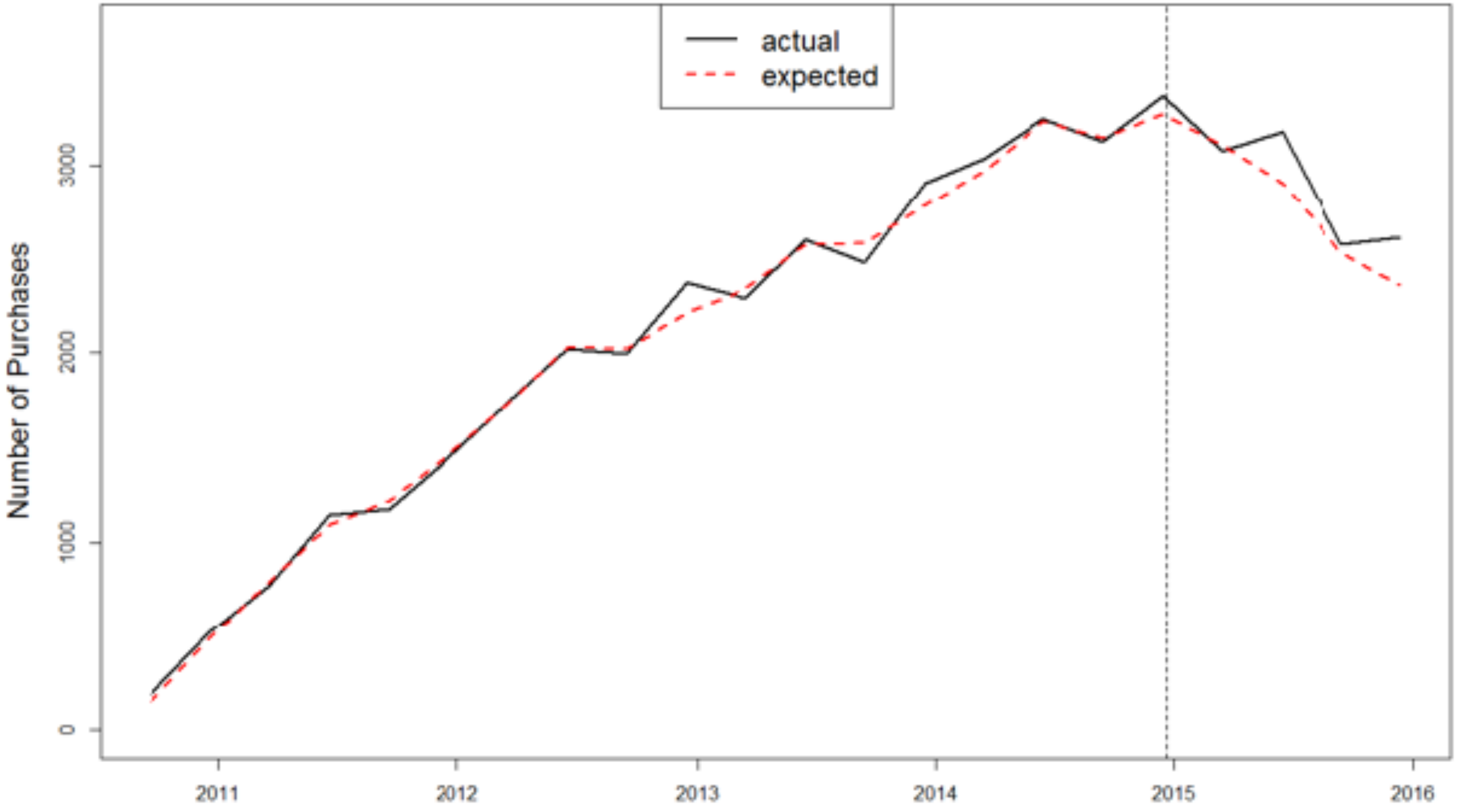
Customer Data

Date	Adds	Active Customers	Average Frequency	Median Spend	Quarterly Revenues
Q3 2010	1,063	1,063	1.176	$118	$738,378
Q4 2010	2,615	2,615	1.272	$128	$941,433
Q1 2011	4,257	4,257	1.348	$126	$852,863
Q2 2011	5,915	5,915	1.445	$125	$873,835
Q3 2011	6,437	6,764	1.487	$125	$865,192
Q4 2011	7,048	7,752	1.495	$126	$1,059,609
Q1 2012	7,438	8,510	1.521	$128	$1,062,051
Q2 2012	7,706	9,118	1.545	$133	$1,133,130
Q3 2012	7,813	9,457	1.587	$136	$1,088,724
Q4 2012	7,790	9,752	1.632	$137	$1,257,208
Q1 2013	7,455	9,746	1.654	$139	$1,186,015
Q2 2013	7,375	9,900	1.679	$140	$1,314,060
Q3 2013	7,497	10,264	1.679	$139	$1,280,353
Q4 2013	7,865	10,746	1.687	$140	$1,494,121
Q1 2014	8,141	11,224	1.707	$142	$1,500,197
Q2 2014	8,142	11,420	1.734	$142	$1,473,638
Q3 2014	8,254	11,703	1.758	$144	$1,427,172
Q4 2014	7,913	11,489	1.801	$144	$1,533,859

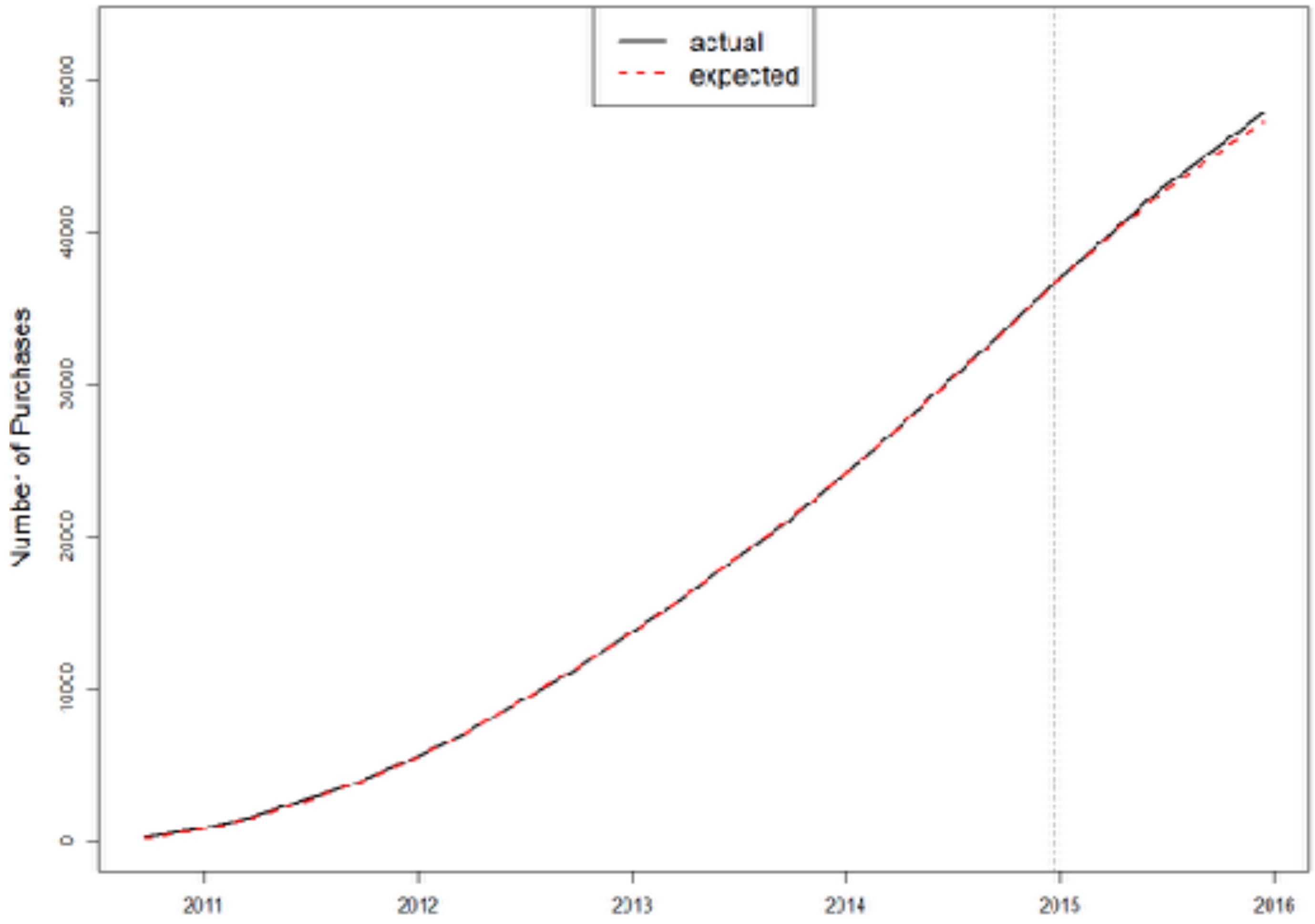
Model Performance (1 of 6): Quarterly Additions



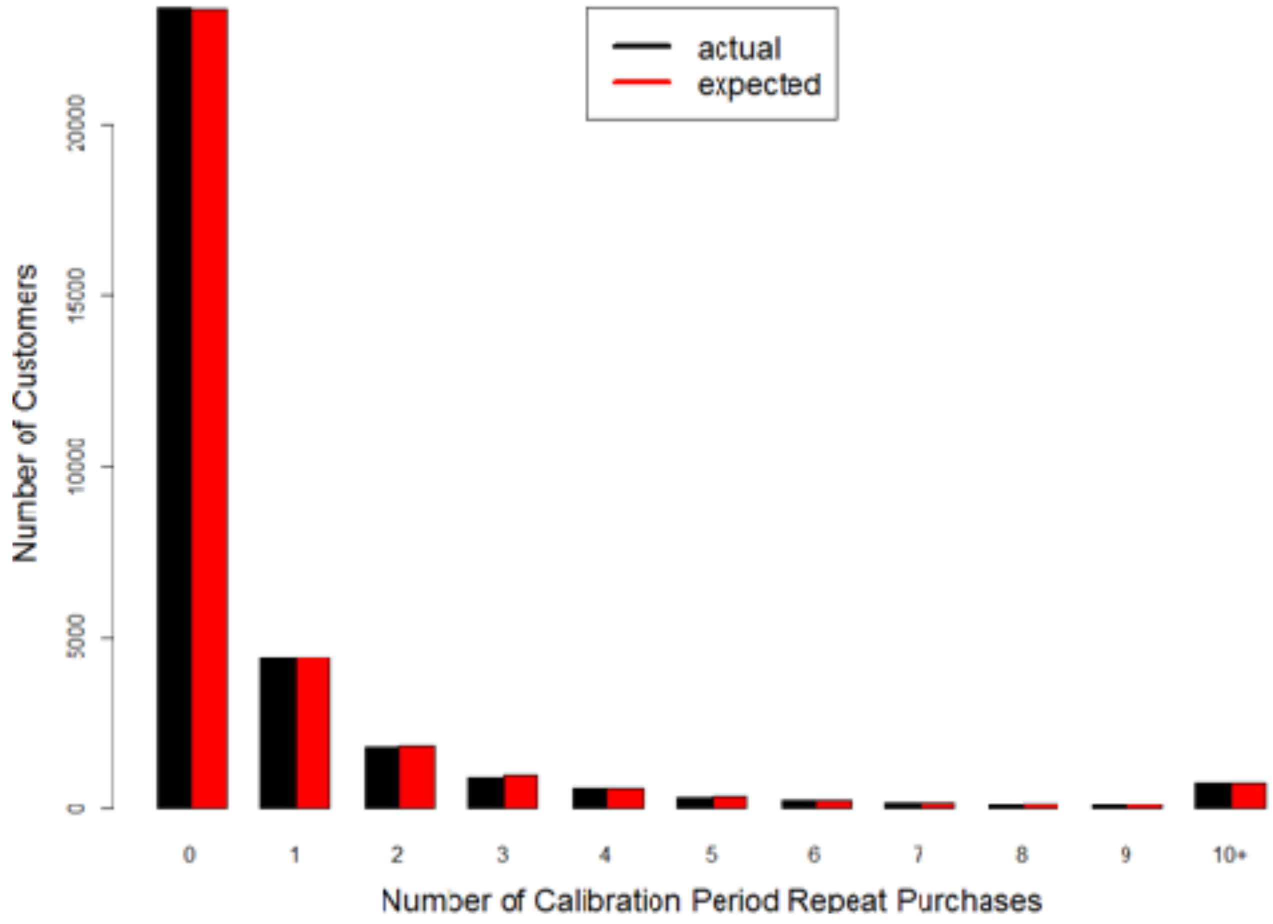
Model Performance (2 of 6):
Tracking Quarter-by-Quarter Transactions



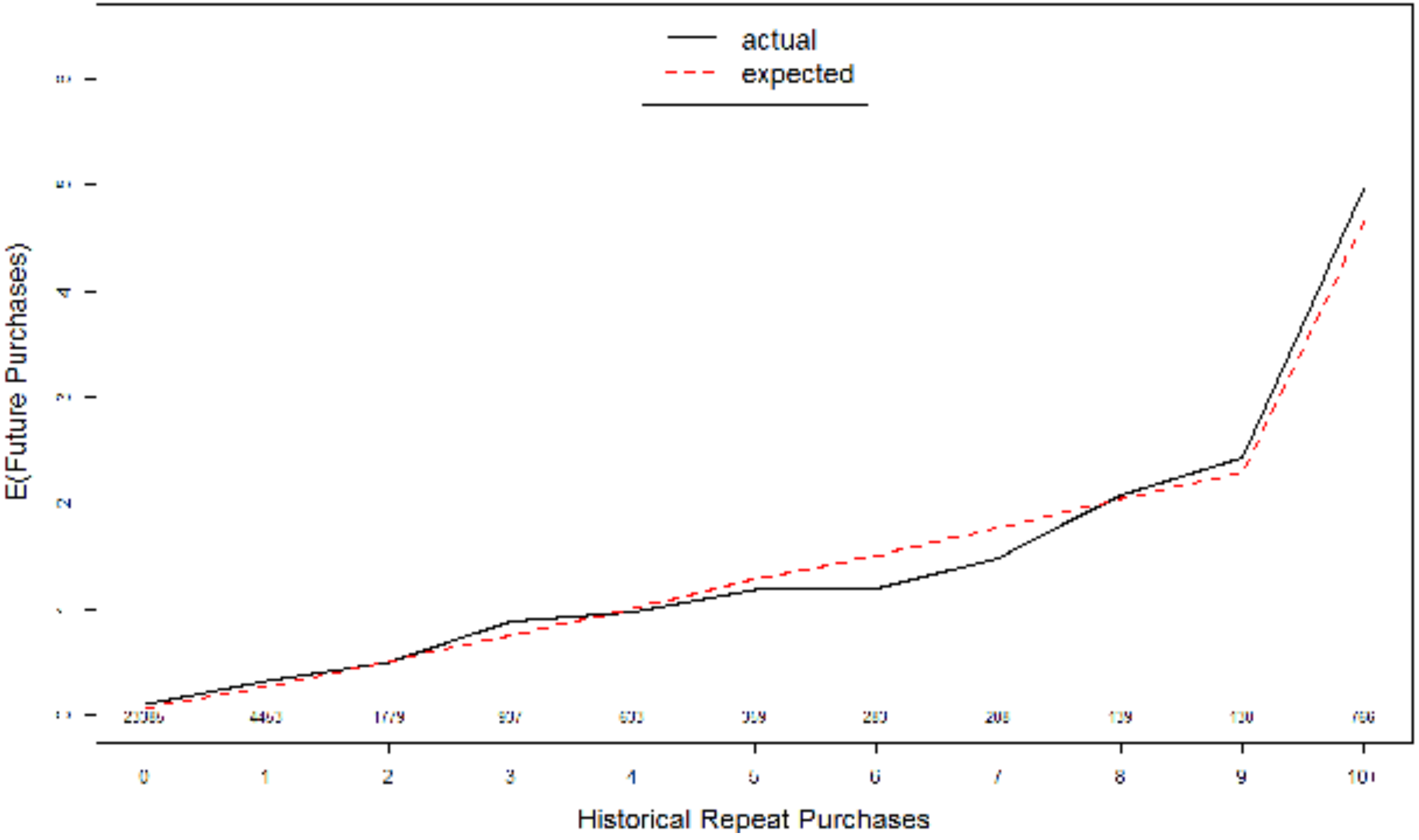
Model Performance (3 of 6): Tracking Cumulative Repeat Transactions



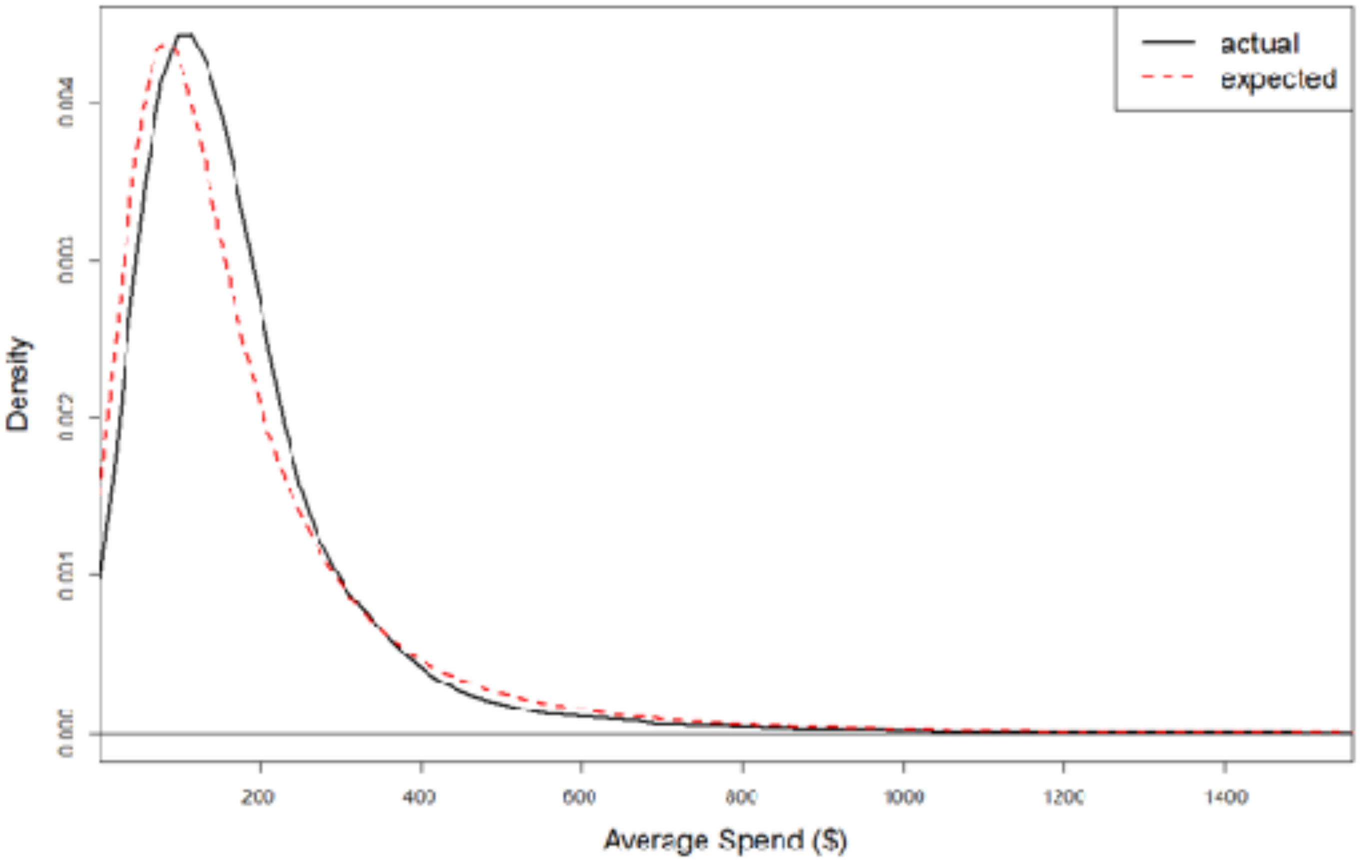
Model Performance (4 of 6): Calibration-Period Frequency Histogram



Model Performance (5 of 6): Conditional Expectations



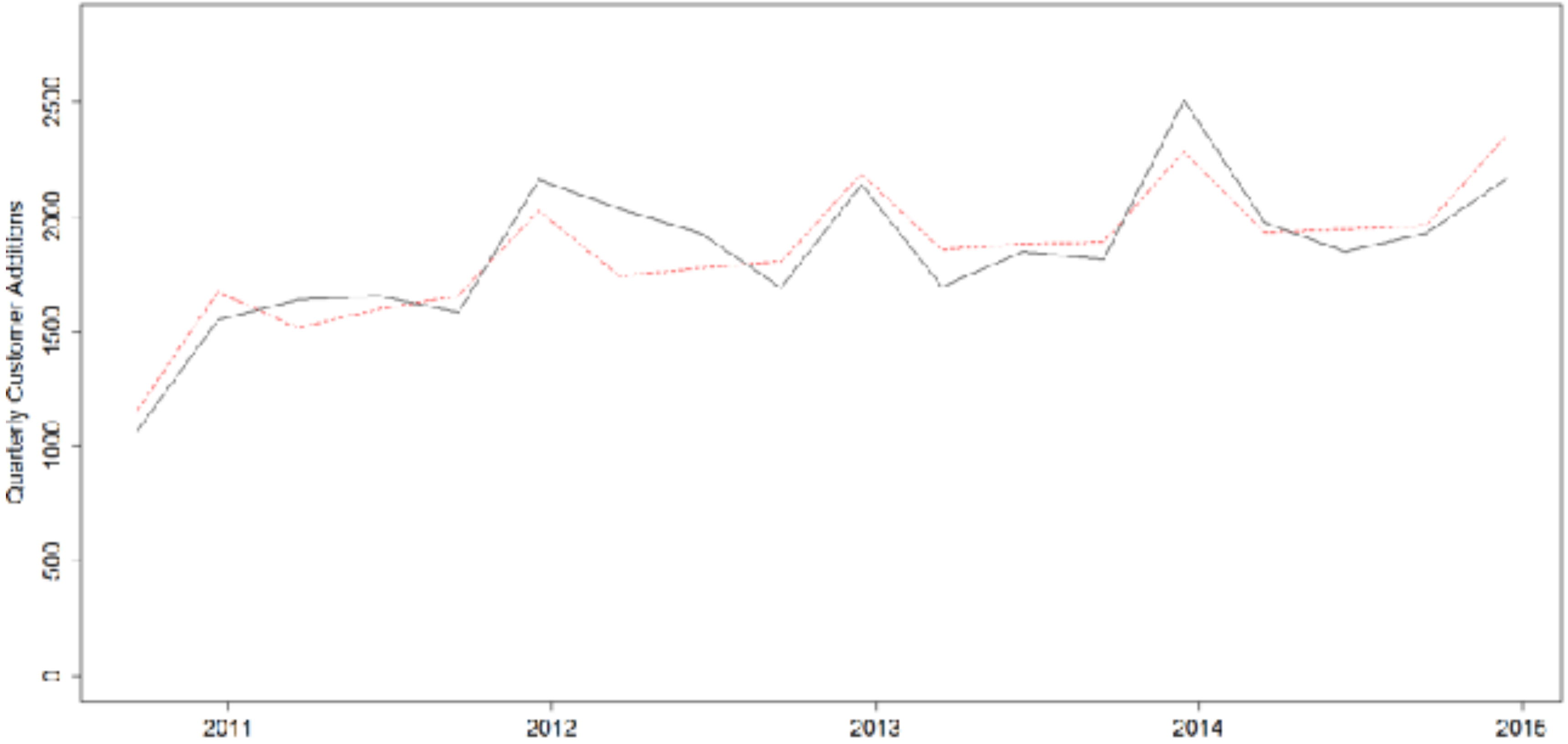
Model Performance (6 of 6): Average Transaction Value Distribution



From model validation to corporate valuation…

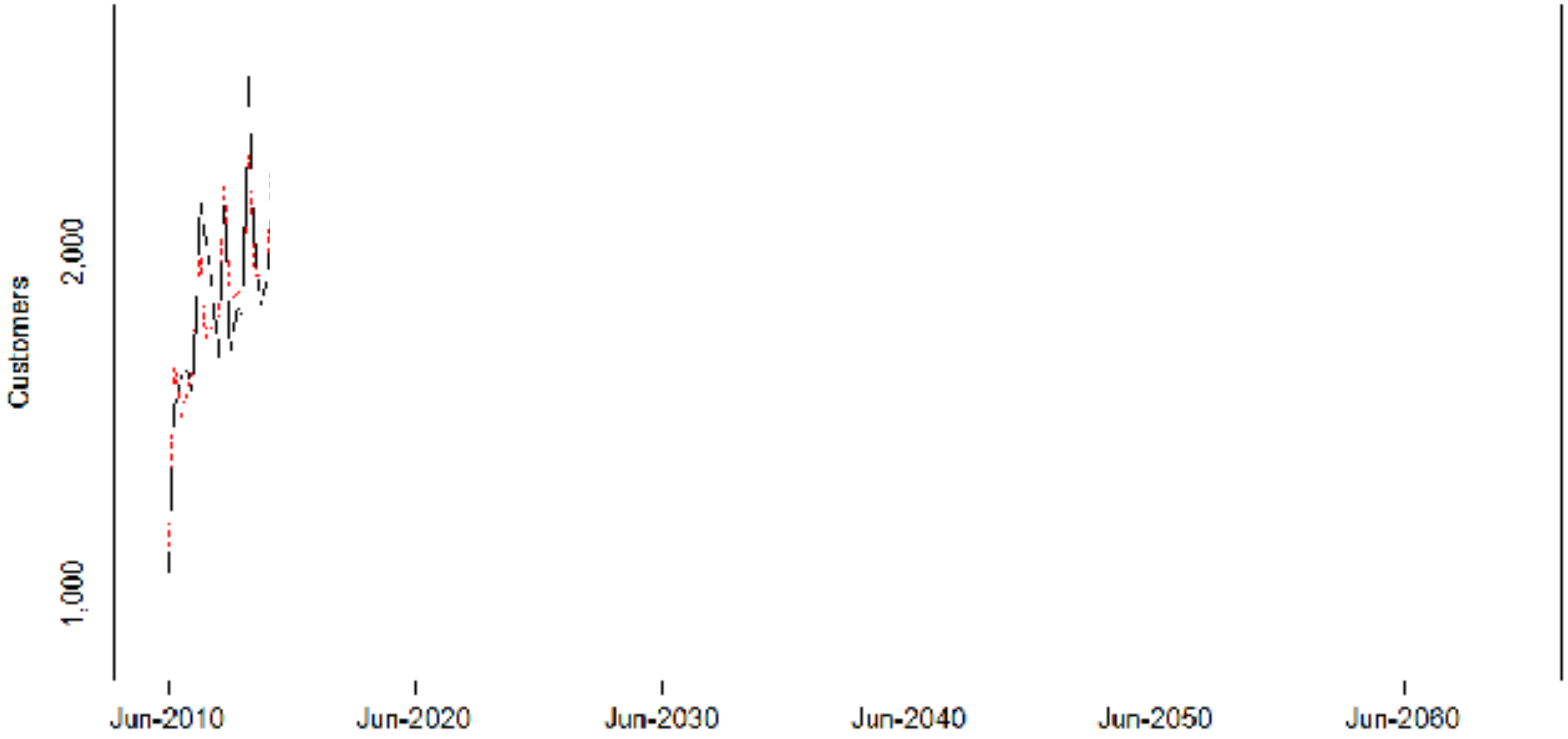
Projecting Revenues

Customer additions: calibration period



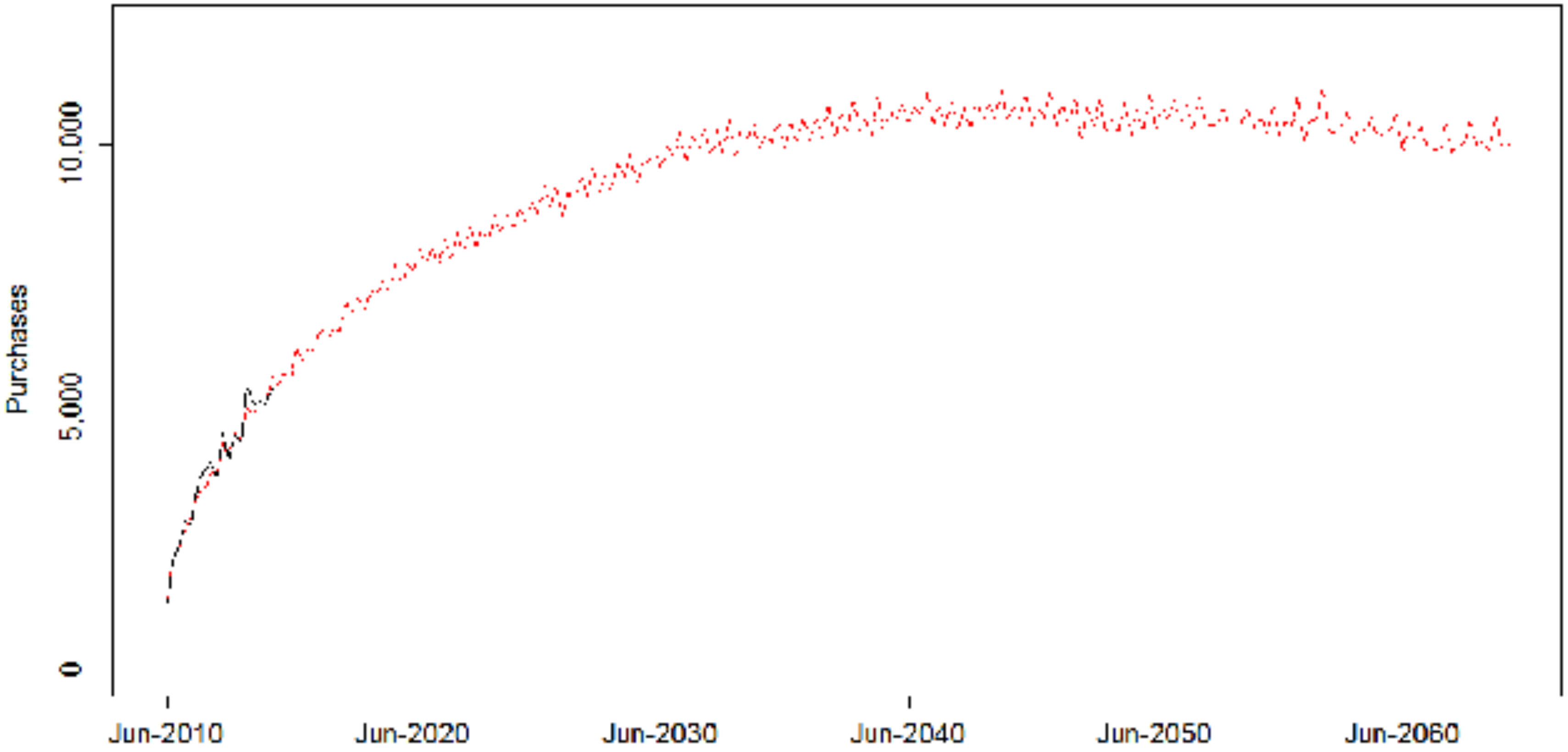
Projecting Revenues

Customer additions: calibration period and projections



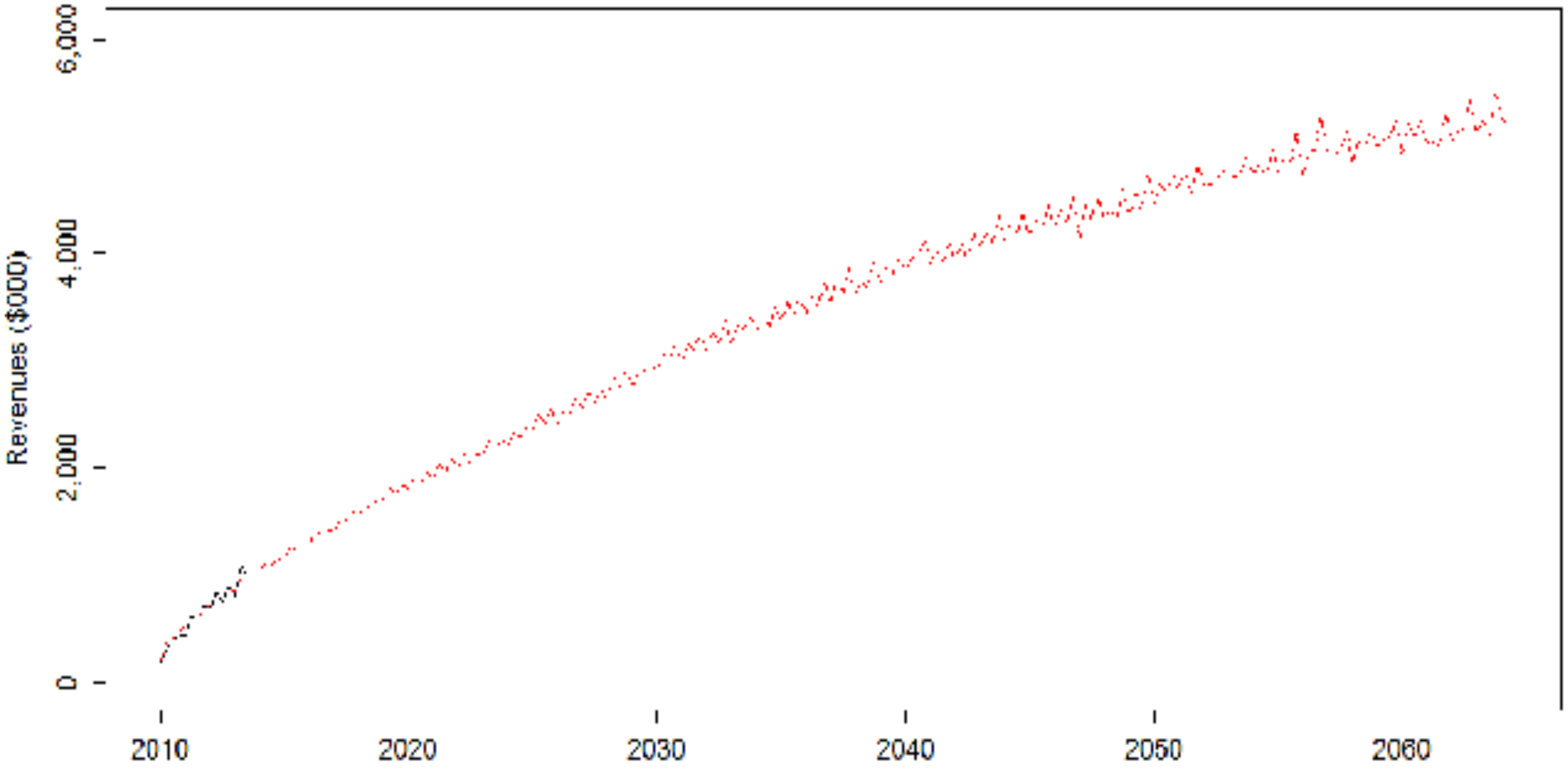
Projecting Revenues

→ Total number of purchases



Projecting Revenues

→ Total revenues



Valuation Results

Assuming:

- Variable contribution ratio of 76.4%
- Customer acquisition cost of $76 per acquisition
- WACC of 6%
- Tax rate of 35%
- Clean balance sheet / no cash flow adjustments

Date				1/7/2015	1/14/2015	1/21/2015	1/28/2015
FCF ($)				$13,025	$13,822	$13,797	$13,772
WACC				6%			
Discount Factor				0.999	0.998	0.997	0.996
PV(FCF) ($)				$13,012	$13,794	$13,756	$13,717
NPV(FCF) =Shareholder Value				$22,825,334			

Other Customer Insights

What else can we learn from this customer-based valuation model?

Value of New Users

Insights into about-to-be-acquired customers:

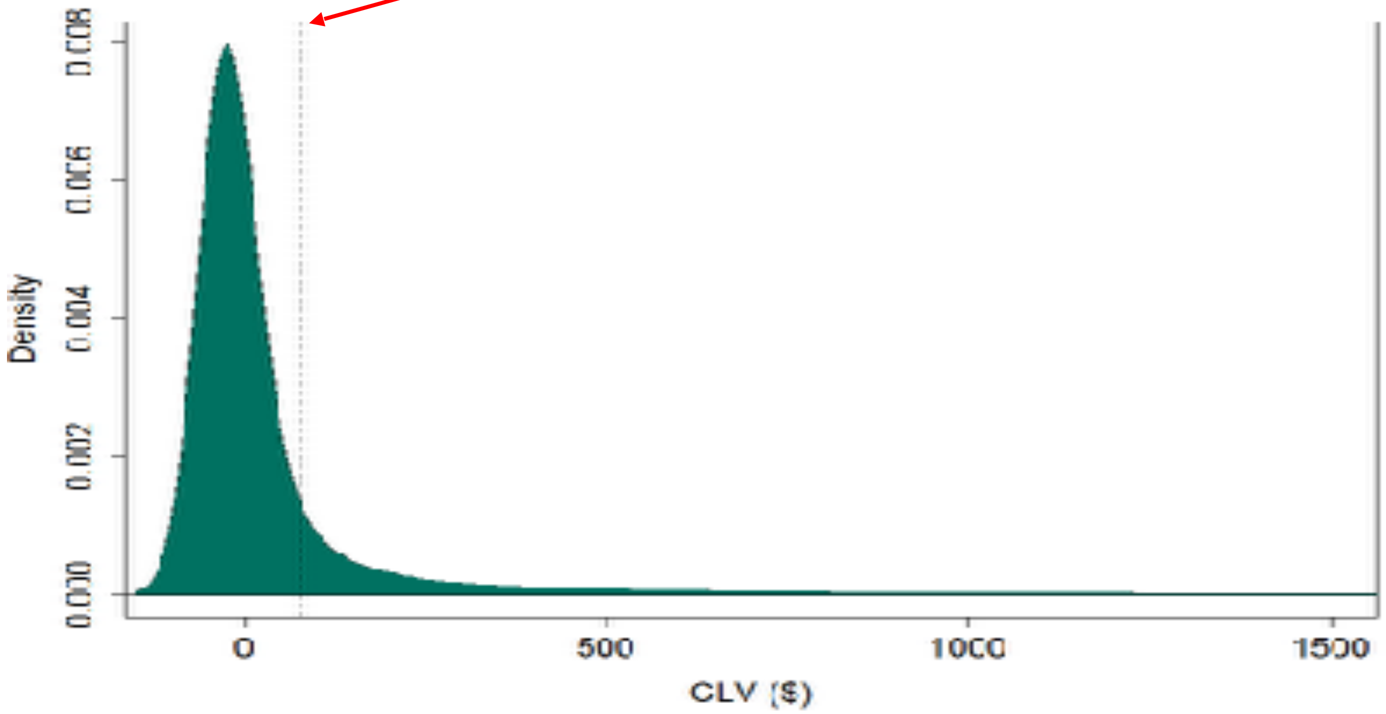
Expected Customer Lifetime Value (CLV): $76.2

Value of New Users

Insights into about-to-be-acquired customers:

Expected Customer Lifetime Value (CLV): $76.2

Distribution of CLV:

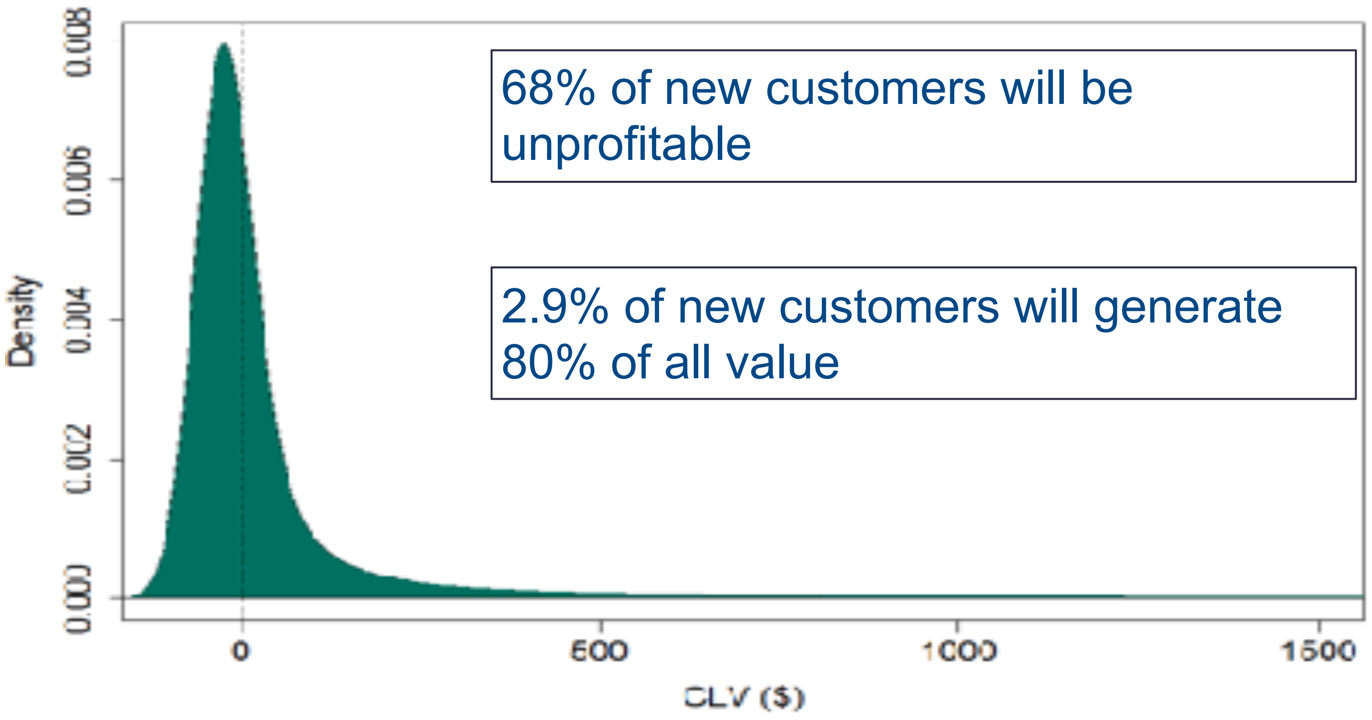


Value of New Users

Insights into about-to-be-acquired customers:

Expected Customer Lifetime Value (CLV): $76.2

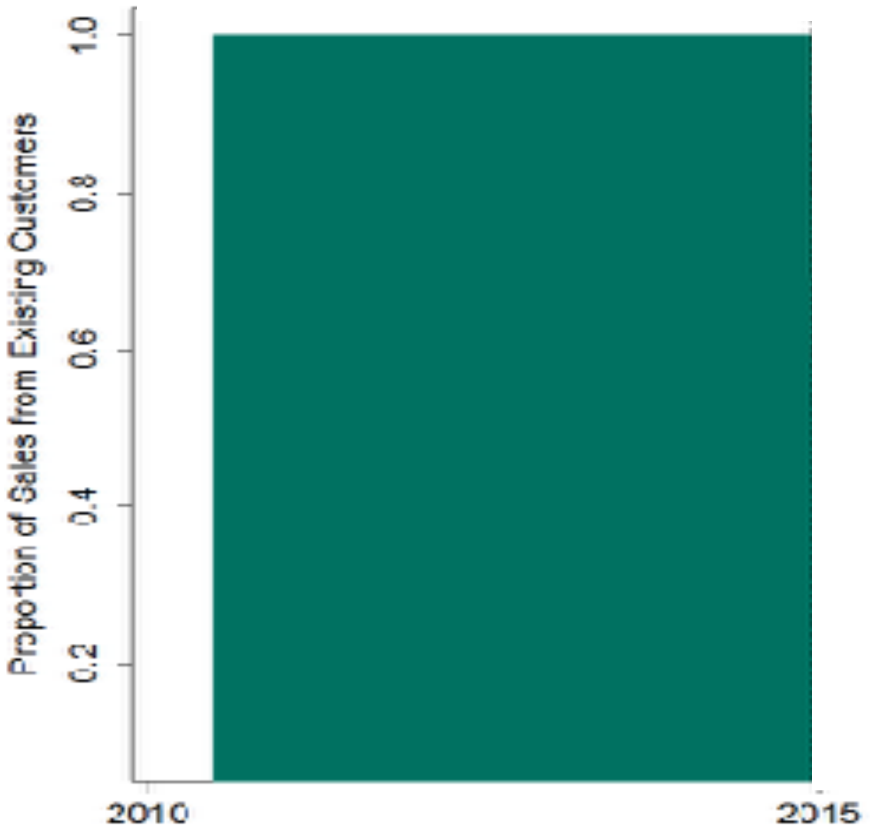
Distribution of CLV:



Existing Customers Versus New Customers

Existing customers worth **$3.1M**, **~15%** of total firm valuation

Proportion of total sales from existing customers:



In 3 years, < **25%** of revenues from existing customers…

Summary

- Customer data can improve company valuation estimates
- Contractual and non-contractual businesses require:
  - Different models
  - Different data
- We propose accurate models specifically suited to both business types
- We recommend the most informative customer data for NC firms (F and AU!)
- Coming up: two public company valuations

Daniel McCarthy

danielmc@wharton.upenn.edu

www.danielminhmccarthy.com

Paper 1: http://whr.tn/CorpValPaper1

Paper 2: http://whr.tn/CorpValPaper2