ONLINE APPENDIX TO

"THE USE AND USEFULNESS OF BIG DATA IN FINANCE: EVIDENCE FROM FINANCIAL ANALYSTS"

Figure A1
List of Alternative Data Vendors and In-house Data Science Teams

We compile a list of data-science teams and alternative-data vendors by combining the vendor list of AlternativeData.org, a platform that connects users to providers of alternative data, with that of J. P. Morgan's 2019 Alternative Data Handbook. The figure below lists all the seven in-house data-science teams and all the 513 alternative-data vendors. *denote in-house data-science teams.

AlphaWise (Morgan Stanley)*
Barclays Investment Sciences and Data Science Team (Barclays)*
Piper Jaffray Web Analytics (PiperJaffray, now Piper Sandler Companies)*
RBC Elements (Royal Bank of Canada)*
UBS Evidence Lab (UBS)*
Wolfe quant team (Wolfe Research)*
Kyber Data Science (Cowen)*

1010Data
7Park
Aberdeen
Accern
Accrete
Aclima
Acuris
AddThis
Advan
Affinity Solutions
AggData
Agribotix
Agricultural Research Federation
Airports Council International
AirSage
ALASA
Alexandria
AllTheRooms
Almax Information Systems
Alpha Hat
AlphaFlow
AlphaLetters
Alphamatician
Alphasense
Alt Hub
Alternate DNS
Amareos
Amass Insights
Amenity Analytics
American Trucking Association
Ampere Analysis
Anonymous Provider
AnthemData
Apertio Technologies
ApexData
AppAnnie
Applaudience
Apptopia
Arab Air Carrier Organization
Arabesque S Ray
ARC
Arch Metrics
AreaMetrics
ARM Insight
Ascend Worldwide Limited
Astutex
Audit Analytics
aWhere
Barchart
BayStreet Research
Beijing Chuang Yi Fang Technology
Beijing UC Science & Technology
Benzinga
Big Byte Insights
Bird.i
Bitly
Bitvore
BizQualify
Black Box (TDn2k)
Black Sky
Bloomberg Tesla Tracker
BMLL Technology
Bombora
Borrell
Boxoffice Media
Brain Company
BrandLoyalties
BrandWatch
Brave New Coin
Brickstream
Bridg
Broughton Capital
Buddy
BuildFax
BuiltWith
Business Intelligence Advisors
Business Monitor International
Capella Space
CB Richard Ellis Inc.
CDU-TEK: Central Dispatching Department of Fuel Energy Complex of Russia
Chain Store Guide Information Services
ChemOrbis
China National Chemical Information Center
China Real Estate Information Corporation
Civic Science
ClipperData
CogniSent
Comlinkdata
CompStak
ComScore
Consumer Edge
Cooltrader
CQG
Crain Communications Inc.
CreditRiskMonitor
Crimson Hexagon
Cropnosis
CropProphet
CrowdThnk
Cruise Analytics
Cuebiq
Cuemacro
CyberStream
Data Guru Limited
Data Simply
Datalogix
Dataminr
Datamyne
Dataprovider.com
DataPulse
Datarama
DataSift
Datastoxx
DataStreamx
DataTrek
DataWeave
DataYes
Dawex
DecaData
DeepAffects
Del Mar Networks
Delphia
DemystData
Descartes Labs
Digital Globe
DigitalMR
Doane Advisory Service
Dodge
Drawbridge
Drewry Shipping Consultants Ltd
Drillinginfo
DroneDeploy
Dun & Bradstreet
EagleAlpha
Earnest Research
Earthcube
EcommerceDB
Edison
Edmunds
EEDAR
Eilers & Krejcik Gaming
Emolument
Endor
EnerKnol
ENGAGE Research
Enigma
Entgroup
EntSight
EODData
EPFR
Epsilon
eSignal
Estimize
Eurekahedge
Euromonitor International
Event Registry
EventVestor
Everest Group
Exante Data
Exerica
Experian Footfall
ExtractAlpha
FactSet Revere
FactSquared
Fashionbi
FastBooking
FeatureX
FHS - Swiss Watch Data
Finweavers
First Data Merchant Services Corporation
First Data SpendTrend
First to Invest
Flexport
FN Arena
FNGO
Foursquare
Fraud Factors
Freestyle Media
FreightWaves
FTR Freight Transport Research Associates
Fysical
GDELT
Genscape
Geocento
GeoQuant
GeoSpark Analytics, Inc
Geospatial Insight
Geotab
GeoWiki
GfK Boutique Research

Global Tone Communication (GTCOM)
GNIP
Good Judgment
GovSpend
Grandata
Granular.ai
Grapedata
Greenwich.HR
Gro Intelligence
GroundTruth (xAd)
GS Dataworks
Guidepoint
Gyana
h2o
Headset
Health Forum
HealthVerity
Heckyl
HFR
Hillside Partners
humanpredictions
Huq Industries
HySpecIQ
ICEYE
ICI
IFI CLAIMS Patent Services
iiMedia Research
IMS Quintiles
Index Marketing Solutions Limited
IndexMath
Inferess
InformaFinancialIntelligence
InfoTEK Publishing House
InfoTrie
Innovata
Inovayt
Insights Data Solutions
InSpectrum
Intelius
Interconnect Analytics
Intermodal Association of North America
International Data Corporation Inc.
Internet Truckstop
Intrinio
Investing.com
IPqwery
iResearch
Irisys
iSentia
iSentium
iSpot
ISS Analytics
ISSB Ltd
Jettrack.io
Jiguang
Jumpshot
JustData
JWN Energy
Kayrros
KD Interactive
Knowsis
Kpler
ktMINE
Kyber Data Science
Landsat on AWS:
Legal Shield
Legis
Lexalytics
LikeFolio
LIMRA
LinkUp
LISTedTECH
ListenFirst
Lota Data
Lucena Research
Lyra Insight
M Science
Magna Global Research
Manfredi & Associates
Manheim
MariData
MarineTraffic
Marinexplore
MarketCheck
MarketPsych
Marketscout Corporation
MASSIVE Data Heights
MasterCard Advisors
MatterMark
Mavrx
Measurable AI
MedMine
Meltwater
Metricle
MIDiA Research
Millennium Research Group Inc.
MixRank
MKT Mediastat
Mobiquity Networks
Money Dashboard
MoneySuperMarket
NAIP
Narrative.io
New Generation Research
Newscred
Newswhip
Nexant Inc.
NEXRAD on AWS
NIC
Nikkei
Nowcast
NPD
Off-Highway Research Limited
Omega Point: a PM platform with AI intelligence
Omney Data
One Click Retail
OpenCorporates
OpenSignal
OpenstreetMap
Optimum Complexity
Orb Intelligence
Orbital Insight
OTAS
Ovum Ltd Us Branch
Owl Analytics
Pacific Epoch (China)
Panjiva
Panvista Analytics
Parsely
PatentSight
PatSnap
Paynxt360
Percolata
PipeCandy
Pitchbook
PlaceIQ
Placemeter
Placer.ai
Planet Labs
Pluribus Labs
Prattle
Predata
Predict HQ
Premonition
PriceStats
PROME
Prosper Insights & Analytics
PsychSignal
QL2
Quad Analytix
Quandl
Quantcube
Quantxt
Quest Offshore
QuestMobile
Quexopa
Rakuten Intelligence
RandomWalk
RavenPack
Real Capital Analytics
Real Estate Data
Realrents
Realyse
Re-analytics
Redbook Research Inc.
RedTech
REIS
RelateTheNews
RelationshipScience
RepRisk
Repustate
RetailNext
Return Path
Reveal Mobile
Revelio Labs
Reviewshake
Rezatec
Rigdata
RigLogix
Rigup
Rook Research
RootMetrics
RS Metrics
RunningAlpha
RVIA
RxData.net
Rystad Energy
Safegraph
Sandalwood
Satellite Imaging Corporation
SatScout
Savvr
SciDex Alpha
Scoop Analytics
Scrapehero
Scutify
Second Measure
Seer Aerospace
Selerity

Semiconductor Equipment & Materials International
Semlab
Sense360
Sensor Tower
Sentifi
Sentiment Trader
Sequentum
SESAMm
Sg2 (MarketPulse)
Sharablee
ShareIQ
ShareThis
ShareThis, Inc.
ShopperTrak
Shoppertrak Rct Corporation
Sigmai
Signal.co
SimilarWeb
SJ Consulting Group Inc.
Sky Watch
Skydeo
Slice Intelligence
Slingshot Aerospace
SmarterWorks
SMB Intelligence
Smith Travel
SNL Kagan
Social Alpha
Social Market Analytics
Space Know
SpaceKnow
Spacelist
SpaceNet on AWS
Spire Global
Spring Pond Partners
Standard Media Index
Statistical Survey
Statlas
Stax
Steel Orbis
StockTwits
STR
StreetLight Data
Suburbia
SumZero
SuperData
SuperFly
Superfly insights
Sustainalytics
Suzy
T.H. Capital
Tailwind Imaging
Tala
Talismatic
TalkingData
Tecnon Orbichem
Tegus
TellusLabs
Teragence
Terra Bella
Terrain Tiles
TerraQuanta
Thasos
The Climate Corporation
The Fertilizer Institute
TheySay
Thinknum
ThinkTopic
TickerTags
Tipigo
Tipranks
TMT Analysis
Towergate Informatics
Trackur
Tradesparq
TransCore
Transport Topics Publishing Group
Trendeo
Tribe Dynamics
Triton Research
TrustData
TrustedInsight
TruValue Labs
Tussell
TVeyes
TXN
TYR Data
Uber Media
Umbra Lab
Unacast
Understory
Unmetric
Upswell Group
Ursa
Urthecast
Venpath
Verbatim Advisory Group
Veronis Suhler Stevenson
Vertical Knowledge
Verto Analytics
Vessel Finder
VesselsValue
Vestdata
VidaMinds
Vigilant
Vortexa
Wall Street Horizon
Wards Automotive Group
Waste Analytics
WDZJ.com
Webhose.io
Wikimapia
Windward
Woodseer
World View
WXshift
Xebral
X-mode
Yewno
YipitData
Yodlee / Envestnet
Zaoshu.io
Zephyr
Zhiwei Data

Figure A2
Analyst Report Example

This figure shows an example of an analyst report explicitly referencing the use of alternative data. We omit the appendices attached to the analyst reports.

UBS | Global Research | 6 April 2017

Powered by UBS Evidence Lab

Walt Disney Co

UBS Evidence Lab: Shanghai Tracking Well -- Supports Emerging Theme Parks Thesis for Disney

Equities

Americas
Entertainment

12-month rating	**Buy**
12m price target	US$130.00
	Prior: US$122.00
Price	US$113.05
RIC: DIS.N BBG: DIS US	

Trading data and key metrics

52-wk range	US$113.39-90.83
Market cap.	US$179bn
Shares o/s	1,581m (COM)
Free float	92%
Avg. daily volume ('000)	2,065
Avg. daily value (m)	US$227.9
Common s/h equity (09/17E)	US$41.4bn
P/BV (09/17E)	4.2x
Net debt / EBITDA (09/17E)	1.1x

EPS (UBS, diluted) (US$)

	09/17E			
	From	To	% ch	Cons.
Q1	1.55	1.55	0	1.55
Q2E	1.38	1.43	3	1.40
Q3E	1.57	1.64	5	1.69
Q4E	1.35	1.28	-5	1.30
09/17E	5.85	5.89	1	5.94
09/18E	6.76	6.76	NM	6.74
09/19E	7.48	7.55	1	7.29

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Theme Parks Drive 67% of the EBIT Growth in our Disney Forecast

We partnered with the UBS Evidence Lab to gauge the health of Shanghai Disneyland ("SDL") as it progresses through its first year and found that the new theme park is tracking quite well. We expect that SDL will drive 29% of the EBIT growth for the Parks division from FY16-21 and that the Parks division, in turn, will drive 67% toal DIS EBIT growth over that same timeframe. With little data available on SDL's progress, this newfound evidence increases our confidence in the near-term outlook for Disney, as well as, critically, its ability to execute with future major Parks capital projects.

UBS Evidence Lab: Remote Sensing and Introducing Network Traffic Analysis

The UBS Evidence Lab correlated two unique data sets to demonstrate healthy trends for SDL: Satellite Photogrammetry to measure visitor parking lot utilization and Network Traffic Analysis to gauge park attraction wait times. Both techniques showed attendance built steadily through the fall and winter towards a very strong Chinese New Year holiday. We reaffirm our FY17 SDL attendance estimate of 11.4m visitors.

Increased Confidence in Sustainabe EPS Growth

While much of the Street is still focused on Disney's likely record FY18 film slate, key at this point, in our view, is whether Disney can sustain high-single digit EPS growth thereafter – we expect it will. We believe investors are underestimating Theme Parks growth prospects, in particular the benefits of SDL (as supported by this report) and a $7B+ Parks capital projects cycle (next up: Pandora opens at Animal Kingdom end of May). Further, we believe ESPN margin concerns are overstated by bears (and ABC retrans upside underappreciated) given over the next 5 years ESPN has almost no new sports cost renewals and almost all of its affiliate renewals, much less near-term virtual MVPD benefits (see our V-MVPD research here and here). Other keys: mgmt's approach to M&A (we do not see a big tech deal); Sep 30th Cablevision renewal; timing of Frozen 2; and timing of Pay 1 Film rights auction (NFLX contract ends end of CY18).

Valuation: Raising Estimates & Target

Due in part to increased Parks confidence, as well as recent film performance, we are raising F2Q17e EPS $0.05 to $1.43 (Street $1.40), FY17e $0.04 to $5.89 (Street $5.94) and our FY17e-FY21e EPS CAGR from 10.0% to 10.5% driven by confidence in the sustainable growth for global theme parks. This drives our DCF-derived target $8 higher to $130 (unch'd are: WACC 8%; growth 2%). DIS trades at 18.5x CY17e EPS, in line with the S&P500 vs. a meaningful premium historically.

Highlights (US$m)	09/14	09/15	09/16	09/17E	09/18E	09/19E	09/20E	09/21E
Revenues	48,813	52,465	55,632	56,964	60,293	63,254	65,233	67,784
EBIT (UBS)	11,540	13,224	14,504	14,870	16,361	17,585	17,933	18,957
Net earnings (UBS)	7,607	8,809	9,382	9,288	10,286	11,152	11,374	12,026
EPS (UBS, diluted) (US$)	4.32	5.15	5.72	5.89	6.76	7.55	7.99	8.79
DPS (US$)	0.88	1.85	1.45	1.67	1.83	2.01	2.21	2.42
Net (debt) / cash	(14,840)	(17,336)	(20,170)	(20,140)	(20,790)	(17,540)	(19,790)	(21,040)

Profitability/valuation	09/14	09/15	09/16	09/17E	09/18E	09/19E	09/20E	09/21E
EBIT margin %	23.6	25.2	26.1	26.1	27.1	27.8	27.5	28.0
ROIC (EBIT) %	19.2	21.4	22.9	23.9	26.0	27.5	27.9	28.8
EV/EBITDA (core) x	11.1	12.3	10.8	11.3	10.3	9.6	9.4	9.0
P/E (UBS, diluted) x	18.3	19.9	17.6	19.2	16.7	15.0	14.2	12.9
Equity FCF (UBS) yield %	4.7	3.8	5.1	4.9	5.8	6.2	6.2	6.7
Net dividend yield %	1.1	1.8	1.4	1.5	1.6	1.8	2.0	2.1

Source: Company accounts, Thomson Reuters, UBS estimates. Metrics marked as (UBS) have had analyst adjustments applied. Valuations: based on an average share price that year, (E): based on a share price of US$113.05 on 06 Apr 2017 18:42 EDT

www.ubs.com/investmentresearch

UBS Research THESIS MAP a guide to our thinking and what's where in this report

OUR THESIS IN PICTURES→

PIVOTAL QUESTIONS

Q: What is the growth outlook for Disney's Theme Parks?

Disney is in the midst of an aggressive (and attractive, in our view) investment cycle at Parks, which we expect will drive a 10% EBIT CAGR at the segment well into the next decade, including what we believe is the current successful launch and first year performance of Shanghai Disneyland.

more→

Q: Are ESPN Fears Overdone?

We believe ESPN fears are overstated due to: 1) subscriber losses are less than Nielsen estimates and are stable-to-improving; 2) it is being included in all virtual MVPD packages; 3) post-F3Q17, there are no major sports renewals for 5 yrs; and 4) it renews virtually its entire affiliate base over the next 5 yrs.

"Addressing Disney's Pivotal Questions..." 2/5/2017→

Q: How will Disney top its recent FY16 film studio success?

We believe Disney will set new records in FY18 with two Star Wars, two Pixar and four Marvel releases, yet tough comps are moderated by the CY19 Pay 1 auction (NFLX ends CY18) and Frozen 2.

"Film on a roll; what might it mean for EPS?" 4/25/2017→

UBS VIEW

We believe investors are underestimating Theme Parks growth -- Disney's Parks build-out the next few years (Avatar, Toy Story, Frozen and Star Wars lands, more Shanghai gates, Hong Kong expansion + 2 new cruise ships) and unique China exposure should continue to drive strong growth in the consumer-facing half of the company (Film, Parks, Consumer Products), even past the record FY18 film slate. We believe bears are overstating margin challenges for ESPN as Media Networks should resume sustainable modest growth from FY18-FY22 as ESPN affiliate renewals pick up (also benefitting ABC retrans) at the same time that ESPN's cost growth slows dramatically. Further, virtual MVPDs could improve ESPN's affiliate revenue trends in 2017 and beyond if they prove popular, as our research suggests.

EVIDENCE

Our bottom-up analysis of pay TV subscriber trends suggests that cord cutting/shaving remain stable; industry sources have confirmed the timing of ESPN affiliate deals and sports rights renewals, and leverage over distribution; and this UBS Evidence Lab study combined with our in-depth analysis of Parks projects provides confidence in the potential for attendance and profit growth.

WHAT'S PRICED IN?

Sentiment has turned much more positive on Disney and the stock has rallied to in line with the S&P 500's valuation. Still, historically Disney has traded at a substantial premium and shares are still not as broadly owned among long-only investors as they should be, in our view, due to concerns around the sustainability of film success and ESPN's subscribers / margins, and management succession planning..

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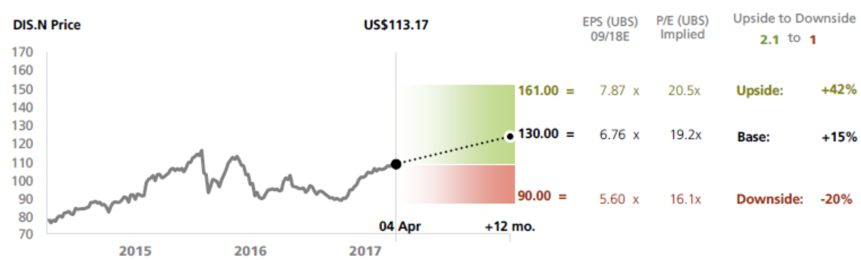
UPSIDE / DOWNSIDE SPECTRUM



Value drivers (FY2018E)	U.S. Cable Net Subscribers	U.S. Cable Net Rate Card	Global Theme Parks EBIT	Film Studio EBIT	CP and Interactive EBTI
$161 upside	0.6%	7.6%	12.4%	42.7%	14.2%
$130 base	-1.4%	6.6%	9.4%	37.5%	8.8%
$90 downside	-3.4%	5.6%	-3.0%	31.9%	4.4%

Source: UBS

more→

COMPANY DESCRIPTION

The Walt Disney Company is a diversified media conglomerate operating media networks, theme parks and resorts, film and TV studios and consumer products businesses. Its broadcast...

more →

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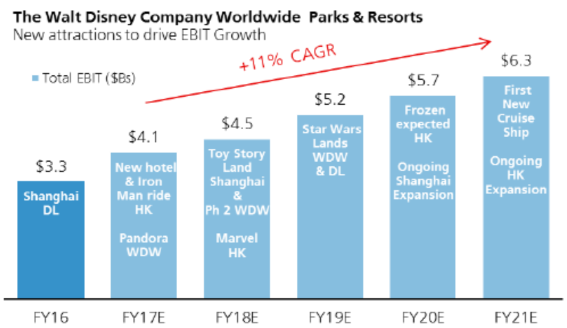
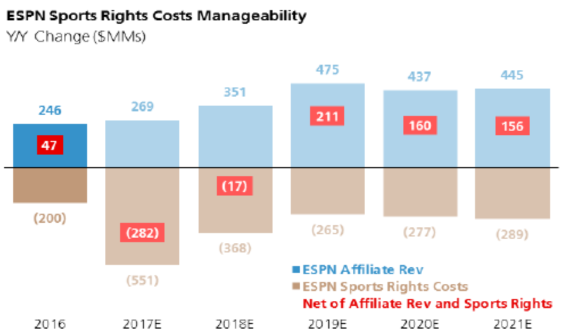
OUR THESIS IN PICTURES

return



The growth of the Shanghai Disneyland theme park and Disney's aggressive continued buildout of its global theme parks footprint (Pandora land, Toy Story land, two Star Wars Lands, two new cruise ships, Hong Kong park expansion, Shanghai expansion) should drive 10% per annum EBIT growth through FY22;

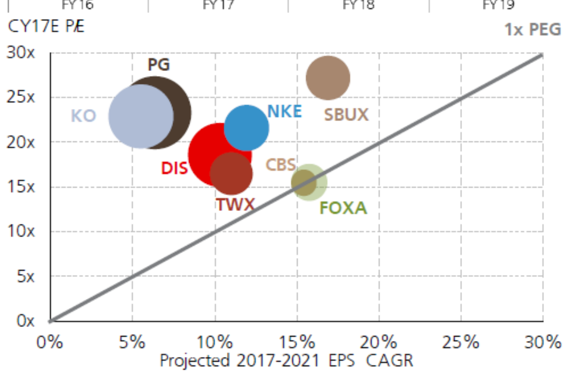


We see ESPN fears as overdone: affiliate revenue growth is stable (cord cutting / skinny bundle impacts steady-to-slightly improving, ESPN in every V-MVPD base tier); its affiliate renewal cycle is restarting (CVC end of FY17, VZ end of CY18, TWC in CY19); and post the NBA step-up (F3Q17 the last impact), there are no major sports rights renewals for 5 years;

Film Studio EBIT Estimates with Expected Film Slate

$2,703	$2,400	$3,300	$3,284
The Force Awakens	Rogue One	The Last Jedi	Mary Poppins Returns
The Good Dinosaur	Dr. Strange	Thor: Ragnarok	Mulan Live Action
	Moana	Wreck It Ralph 2	Gigantic
Zootopia	Beauty & the Beast	Coco	Captain Marvel
Captain America 3	Guardians 2	Avengers 3	Avengers 4
The Jungle Book	Pirates 5	Black Panther	Star Wars Ep 9
Finding Dory	Cars 3	The Incredibles 2	Toy Story 4
Alice: Through...		Han Solo Standalone	Indiana Jones
Pete's Dragon		Ant Man 2	Frozen 2?
FY16	FY17	FY18	FY19

Core to our Disney thesis has been that 2017 Film results are likely to be better than feared, while 2018's slate is likely to easily break new records. While Beauty and the Beast has proven to be the big hit we had hoped for, we still see the potential for Guardians 2, Pirates 5 and Cars 3 to exceed expectations. With investors already beginning to discount the likely growth from the FY18 film slate, we are starting to gauge FY19 in more detail. While having tough comps, we still see strength in FY19 with key Star Wars and Marvel storyline finales, Toy Story 4 (vs. Cars 3), potentially Frozen 2 and a likely step-up from a new Pay 1 deal (the NFLX deal ends end of CY18); and



While DIS trades at a premium to media conglomerates, it trades in line with large cap consumer companies, which many use as a comp set, and at a lower premium to the S&P500 than it has historically. We do not expect Disney to launch highly dilutive M&A, but rather that it will continue its stock buyback pace.

Sources for exhibits above: Company data, UBS Research estimates, Factset, Boxofficemojo.com

PIVOTAL QUESTIONS

return ↑

Q: What is the growth outlook for Disney's Theme Parks?

UBS VIEW

Disney is in the midst of an aggressive investment cycle at its global theme parks, led by Shanghai Disneyland and new attractions/cruise ships opening FY18-FY22, which, in addition to pricing levers and potential pension/OPEB moderation, should drive an 11% EBIT growth CAGR at the segment.

EVIDENCE

UBS Evidence Lab Remote Sensing and Traffic Monitor analysis shows Shanghai Disneyland is tracking well. Further, our analysis of Disney's announced park projects indicates that a multitude of new high-margin, high return attractions will be opening steadily through early next decade.

WHAT'S PRICED IN?

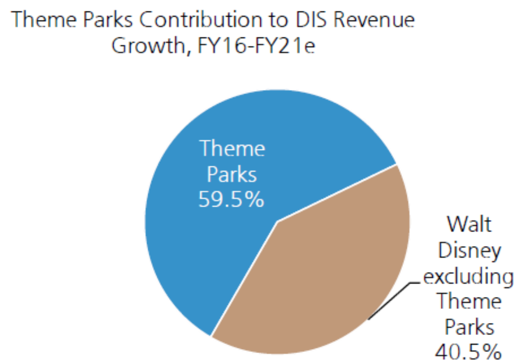
We believe investors have been distracted by ESPN secular concerns, and that only longer term investors have begun to consider the potential growth prospects of the Theme Park segment.

Theme Parks Expected to Drive the Majority of Growth for Disney

Disney has a unique position in Theme Parks, with the leading scale and scope of its parks, its vast array of characters and franchises to leverage, the global nature of its brands allowing for emerging market expansion, and the differentiated experiences that its parks and hotels offer.

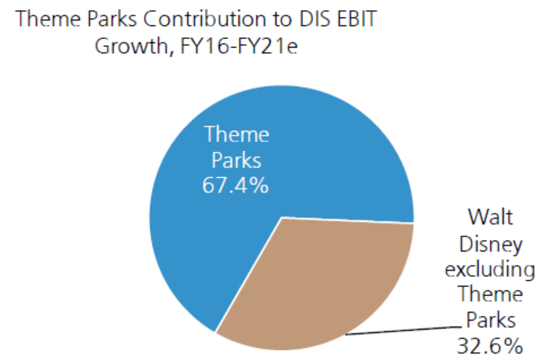
The SDL resort is just one of several growth initiatives that management has outlined at its global theme parks division. We see over $7b in capital projects over the next five years, all of which should enhance Disney's Parks capacity and attractiveness to fans around the world. After decades where growth was led by cable networks (ESPN) and more recently by its success in filmed entertainment and consumer products, we expect 67% of EBIT growth between now and FY21e to come from global theme parks.

Figure 1: Theme Parks will drive 60% of Walt Disney Revenue Growth through FY21e…



Source: UBS estimates

Figure 2: …and we see the Theme Parks segment contributing 67% of Disney's EBIT growth through FY21



Source: UBS estimates

Shanghai Disneyland Tracking Well

We consider Shanghai Disneyland ("SDL") crucial to our Parks thesis for Disney, both in terms of its growth contribution to the Parks segment (40% of FY17 Parks EBIT growth) and as an important gauge of Disney's ability to execute on major capex projects. Since SDL opened on June 16, 2016 there has been limited information available around attendance at the park other than the occasional management anecdote. In early March, CEO Bob Iger remarked that SDL is closing in on 8m guests, on its way to more than 10m in year 1. While management commentary is getting more aggressive, we believe targets have been too conservative and we still expect SDL will hit 11.4m guests in FY17.

Figure 3: Management Comments on Shanghai Visitation

Date	Visitors to Date	Daily Pace to Date	Daily Pace since last update	Year 1 Target
11/10/16	4m	27778	27778	
02/07/17	7m	30303	34483	Potentially Exceed 10m
03/08/17	Almost 8m	30229	29032	More than 10m

Source: UBS, Alpha-sense, Management commentary

Therefore, we decided to enlist the UBS Evidence Lab to monitor SDL using two distinct capabilities to gauge likely attendance trends: Satellite Photogrammetry to measure parking lot utilization and App Analytics to analyze attraction wait times. We found these two data techniques yield very interesting insights into the attendance trends at SDL.

**UBS Evidence Lab provides our research analysts with rigorous primary research. The team conducts representative surveys of key sector decision-makers, mines the Internet, systematically collects observable data, and pulls information from other innovative sources. They apply a variety of advanced analytic techniques to derive insights from the data collected. This valuable resource supplies UBS analysts with differentiated information to support their forecasts and recommendations—in turn enhancing our ability to serve the needs of our clients.*

UBS Evidence Lab Network Traffic: Wait Time Monitor

Methodology Overview

UBS Evidence Lab Network Traffic is a product suite that measures the traffic or usage pattern of a particular asset or resource within specified time periods along some network. Example includes auto traffic, plane traffic, and point of attraction (POI) wait times Traffic patterns could comprise measures of current usage, time spent waiting to utilize the resource, and measures of congestion, among others. Time periods could be specified in seconds, minutes, days, weeks, etc. depending on the appropriate use patterns necessary to identify inflections in usage patterns.

Network Traffic problems or questions span many use-case including: measuring usage patterns over time, measuring the competitive impact for a particular resource driven by the introduction of a competing resource, determining bottlenecks / choke points / critical times related to a particular resource, dimensioning breakeven time to recover investments from introducing or replacing a resource, etc. Essentially these tools and techniques factor network traffic including availability, measures of movement, competition, to help dimension the cost or revenues related to specific resources.

For the Disney Shanghai report, UBS Evidence Lab developed a Wait Time Monitor, aggregating hourly wait times posted for 24 Disney Shanghai rides and attractions collected between the opening and closing time each day. The dataset in this report covers the 13 week period from November 6 through January 29. Wait time data was juxtaposed to car park utilization measured via remote sensing for validation purposes. The UBS Evidence Lab also segmented the data into common time period cohorts to view, for example, differences between weekday and weekend traffic trends at the park.

Data Sources

The UBS Evidence Lab gathered data from thousands of individual sources including web mining, FOIA request, business listing databases, in person collection, and other syndicated sources.

For the Disney Shanghai report, UBS Evidence Lab collected real time wait times posted for all attractions at the Disney Shanghai resort from the official Disney website and related mobile apps. UBS Evidence Lab also vectorised images of the park so present the data spatially.

Data Quality

All the business rooftop and wait time data is loaded into a global data warehouse. Before processing the analytics, several data quality routines and processes are run to validate and enhance the raw data set. Any dataset that fails a validation check is flagged or cleansed until quality standards are met. Importantly, to the best of its ability, the UBS Evidence Lab also audits all harvested to reported figures where possible.

UBS Evidence Lab Remote Sensing

Methodology Overview

UBS Evidence Lab Remote Sensing practice is a suite of products that deal primarily with satellite imagery but also includes aerial survey, unmanned aerial imagery, and land-based monitoring sensors such as pollution measurement or weather station measurement. Sensors utilized include optical, thermal, radar, sonar, LIDAR, hygrometer, anemometer, and pyranometer among others. The UBS Evidence Lab uses cutting edge techniques to analyze remote sensing data including computer vision/trained modeling, pattern recognition (PCA, Iso-Cluster, class probability), point cloud interpretation, and CAD estimation among others. The analyses technique can be used to count object such as cars, trains, ships, and construction milestones; or derive volumetric measurements such as measuring the surface area of reservoirs, the volume of coal piles, and the depth of mine pits; or for general classification such as measuring urbanization, agriculture and overall land use urbanization, agriculture, land use, and heat signatures.

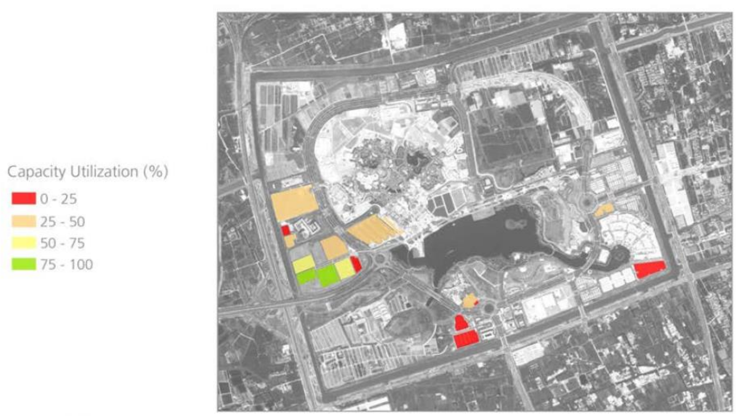
For the Disney Shanghai report, UBS Evidence Lab vectorised the parking lots of the park and developed geofences and photogrammetry based algorithms to count the cars and buses and ultimate measure the utilization rates of the parking lots.

Map of Shanghai Disneyland Resort

Source: UBS Evidence Lab

UBS Evidence Lab Estimated Parking Lot Utilization of 47% at Shanghai Disneyland Resort on the Monday before Chinese New Year (1/23/17)

Disney Shanghai: Parking Lots Capacity Utilization 23 Jan 2017

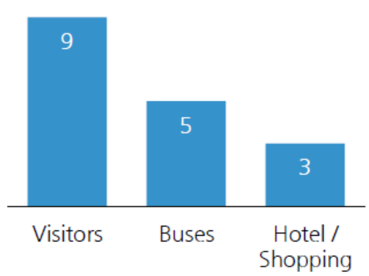


powered by UBS Evidence Lab

Remote sensing shows parking lot utilization has improved steadily since the summer

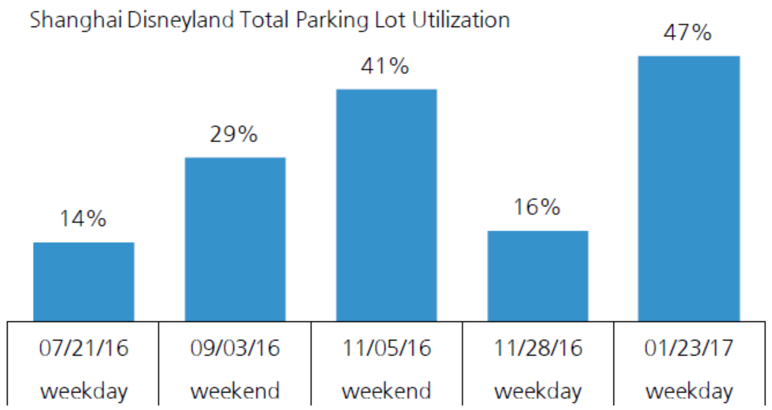
Using Satellite Photogrammetry, the UBS Evidence Lab captured images of Shanghai Disneyland on five dates since the park opened last summer. Using these images, they identified and then analyzed parking lots, counting the number of parked cars in order to ascertain visitation trends. Excluding employee lots, there are 17 different lots currently in use at the resort. All of the images were captured between 10am and 11am local time to allow for consistency.

Figure 4: Shanghai Disneyland Resort Parking Lots in Use



Source: UBS Evidence Lab

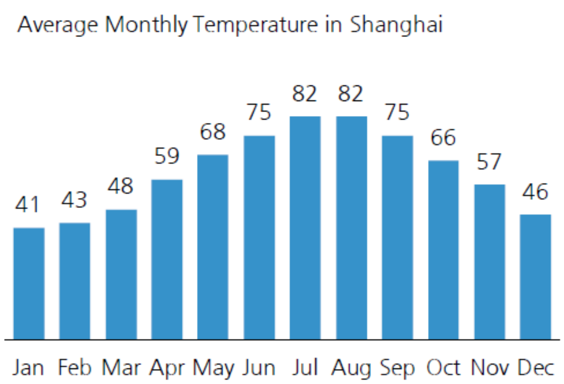
Figure 5: Shanghai Disneyland parking lot utilization has steadily improved since last summer



Source: UBS Evidence Lab

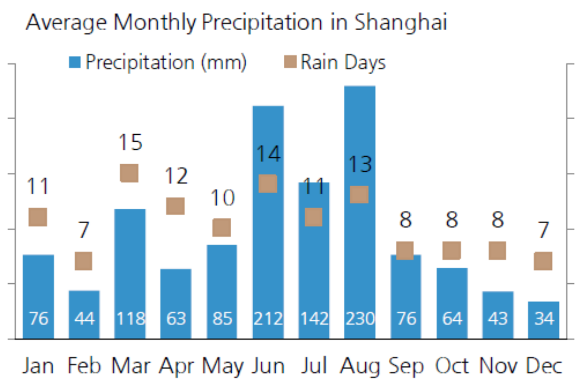
Images from five dates between July and January showed steady improvement in lot utilization. Weekdays were light on the two days we checked in July and November, as one might expect given the work week and school calendar, respectively. However, weekends showed steady improvement from September to early November as the weather improved.

Figure 6: Shanghai temperature peaks in July-August…



Source: travelchinaguide.com

Figure 7: …when the area also sees heavy precipitation



Source: travelchinaguide.com

The weekend days we analyzed ran at 2-3x the parking lot capacity utilization of the weekdays we measured, which we found encouraging given single day tickets are priced $15-$20 higher on weekends and holidays than standard weekday tickets.

Figure 8: Disney charges peak rates for weekend tickets at Shanghai Disneyland

Ticket Prices for Top Theme Parks in China

Park	Ticket Type	City	Local Price Adults	Local Price Children	USD Price Adults	USD Price Children	Currency	Exchange Rate	Notes
Hong Kong Disneyland		Hong Kong	589.0	419.0	75.9	54.0	HKD	0.13	Theme Park
Shanghai Disneyland	**Peak***	**Shanghai**	**499.0**	**375.0**	**72.2**	**54.3**	**CNY**	**0.14**	**Theme Park**
Ocean Park		Hong Kong	438.0	219.0	56.4	28.2	HKD	0.13	Marine park
Chimelong Ocean Kingdom	Peak	Zhuhai	380.0	265.0	55.0	38.4	CNY	0.14	Marine park
Shanghai Disneyland	**Standard**	**Shanghai**	**370.0**	**280.0**	**53.6**	**40.5**	**CNY**	**0.14**	**Theme Park**
Chimelong Ocean Kingdom	Standard	Zhuhai	350.0	245.0	50.7	35.5	CNY	0.14	Marine park
Chimelong Safari Park	Peak	Zhuhai	300.0	210.0	43.4	30.4	CNY	0.14	Theme Park
Chimelong Paradise		Guangzhou	250.0	175.0	36.2	25.3	CNY	0.14	Theme Park
Chimelong Safari Park	Standard	Zhuhai	250.0	175.0	36.2	25.3	CNY	0.14	Theme Park
Chimelong Water Park		Guangzhou	200.0	140.0	28.9	20.3	CNY	0.14	Theme Park
Happy Valley		Shenzhen	200.0	100.0	28.9	14.5	CNY	0.14	Theme Park
Happy Valley		Beijing	180.0	150.0	26.1	21.7	CNY	0.14	Theme Park
Window of the World		Shenzhen	160.0	80.0	23.2	11.6	CNY	0.14	Theme Park
Polarland		Harbin	120.0	60.0	17.4	8.7	CNY	0.14	Marine park

Source: Company theme park ticketing websites and travelchinaguide.com. *Peak period includes weekends and holidays

We saw the highest utilization (47%) on 1/23/17, the Monday prior to the Chinese New Year Holiday in late January, consistent with management commentary that the park operated at full capacity during the Chinese New Year Holiday, which officially runs from January 27th to February 2nd.

Figure 9: Local Holidays and Events in Shanghai

Begins	Ends	Event	Description
CY16			
1-Oct	**7-Oct**	**National Day Holiday**	**National Holiday**
15-Sep	**17-Sep**	**Mid Autumn Festival Holiday**	**National Holiday**
CY17			
1-Jan	**2-Jan**	**New Years Holiday**	**National Holiday**
27-Jan	**2-Feb**	**Chinese New Year Holiday**	**National Holiday**
27-Mar	16-Apr	Peach Blossom Festival	Shanghai Festival
30-Mar		Longhua Temple Fair	Shanghai Festival
2-Apr	**4-Apr**	**Qingming Festival Holiday**	**National Holiday**
7-Apr	9-Apr	Formula 1 Grand Prix	Shanghai Sporting Event
1-May		**May Day or Labor Day**	**National Holiday**
18-May	21-May	International Tea Expo	Shanghai Festival
28-May	**30-May**	**Dragon Boat Festival**	**National Holiday**
1-Oct	**8-Oct**	**National Day Holiday**	**National Holiday**
4-Oct		**Mid Autumn Festival Holiday**	**National Holiday**

Source: travelchinaguide.com

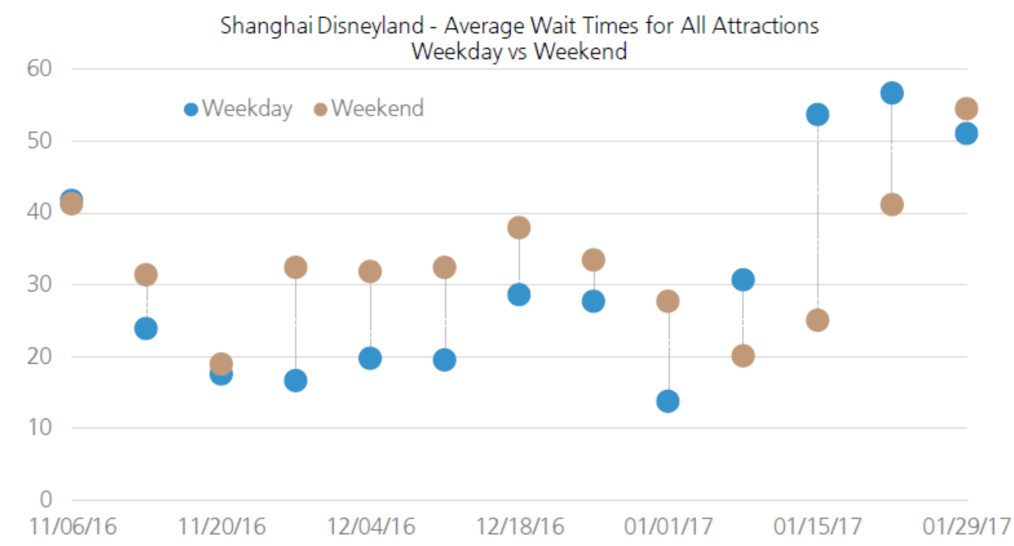
Note, the utilizations of the parking lots being low is due to the excess capacity we expect was built to handle the expansion of the Theme Park over time, and due to a significant number of visitors arriving via public train access; the city built a Metro station to support traffic into the theme park. Still, we were able to leverage the Chinese New Year "at capacity" data point from management to baseline what level of attendance parking lot utilization might represent. By our estimates, about one-half of visitors arrive via train.

App Traffic Monitor Data Shows Strength into the Chinese New Year Holiday

The UBS Evidence Lab analyzed App data that provides wait times for the 24 Shanghai Disneyland attractions that have wait times associated with them. Our analysis covers the thirteen-week period from November 6, 2016 through January 29, 2017.

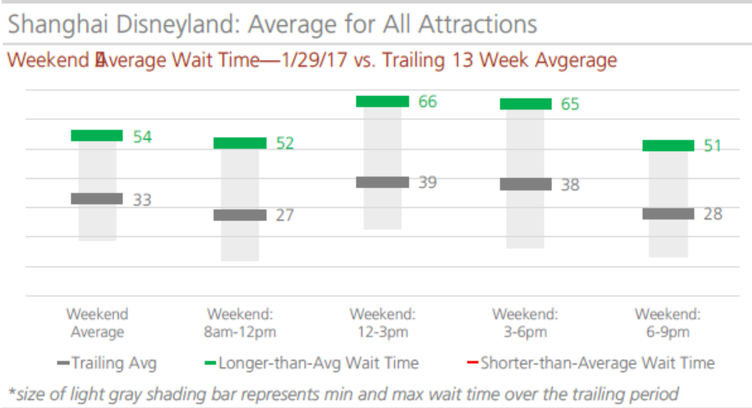
Not surprisingly, ride wait times are longer on the weekends than weekdays and that correlates with our parking lot utilization data. Average ride wait times were fairly steady between November and December, before rising throughout January in the run up to the Chinese New Year Holiday. The week of Chinese New Year saw the longest wait times in the thirteen weeks for which we have data.

Figure 10: Wait times were longer on weekends, until the weeks leading into the Chinese New Year



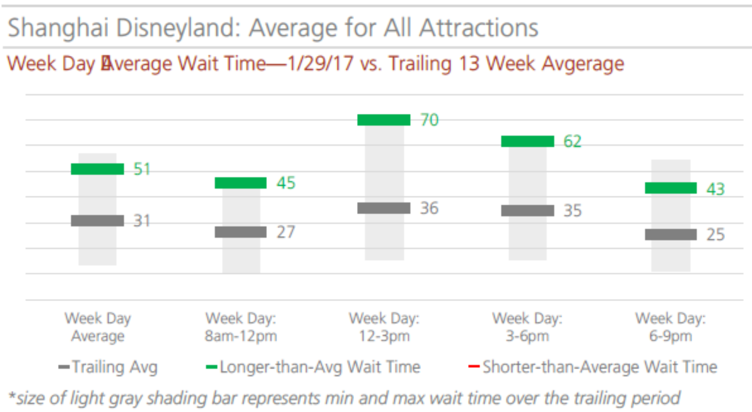
Source: UBS Evidence Lab

Figure 11: Wait times peak mid-day, but are fairly steady throughout the day



Source: UBS Evidence Lab

Figure 12: Weekday average wait times were typically a few minutes less than on weekends, except during the Chinese New Year Holiday in late January



Source: UBS Evidence Lab

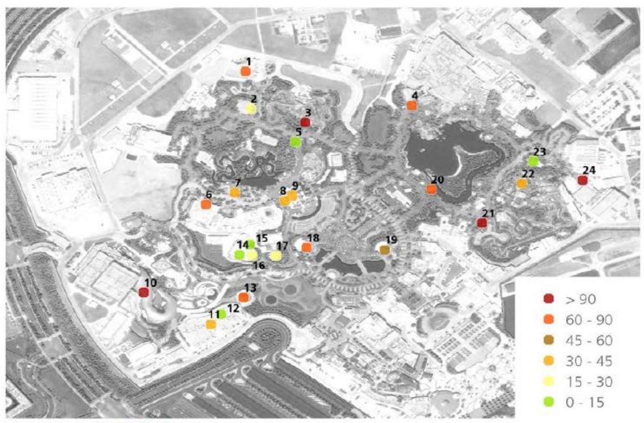
Figure 13: Average Wait Time by Attraction at Shanghai Disneyland Resort During Chinese New Year Holiday Weekend (average 1/28/17-1/29/17)

Network Traffic:

Disney Shanghai

Average Wait Time — Weekend Average for Week of 01/29/2017

Disney Shanghai: Waiting Times - Weekends Week: 29-Jan-17

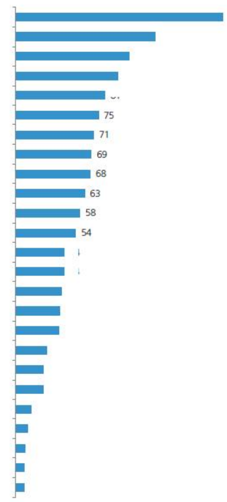


powered by UBS Evidence Lab

Network Traffic:

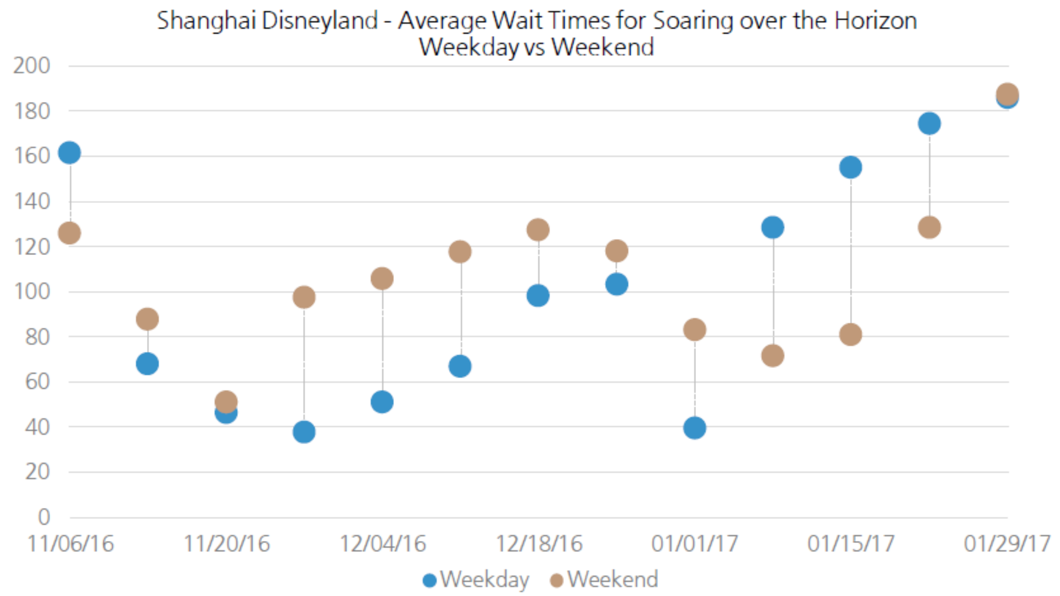
Disney Shanghai

Average Wait Time — Weekend Average for Week of 01/29/2017



Source: UBS Evidence Lab

Figure 14: Soaring Over the Horizon sees the longest wait times of any attraction at the resort – and wait times for the attraction ramped steadily into Chinese New Year, even on weekdays



Source: UBS Evidence Lab

Overall, the improvement late fall in attendance tracking for SDL following by a strong Chinese New Year is encouraging, and, in our view, supports a stronger growth potential for the Shanghai Park than many investors might be discounting. Further, the success of SDL with all of its complexities and scale is encouraging, especially with Park capital projects from here being more bolt-ons to existing businesses.

Figure A3
Alternative Data Usage by Category and Industry

This figure plots alternative data usage across the 8 alternative data categories and 9 GICS 2-digit level industries. The color intensity of each cell represents the percentage of alternative data reports, which is indicated by the color gradient scale on the right side of the chart. Darker shades indicate higher percentages, while lighter shades indicate lower percentages.

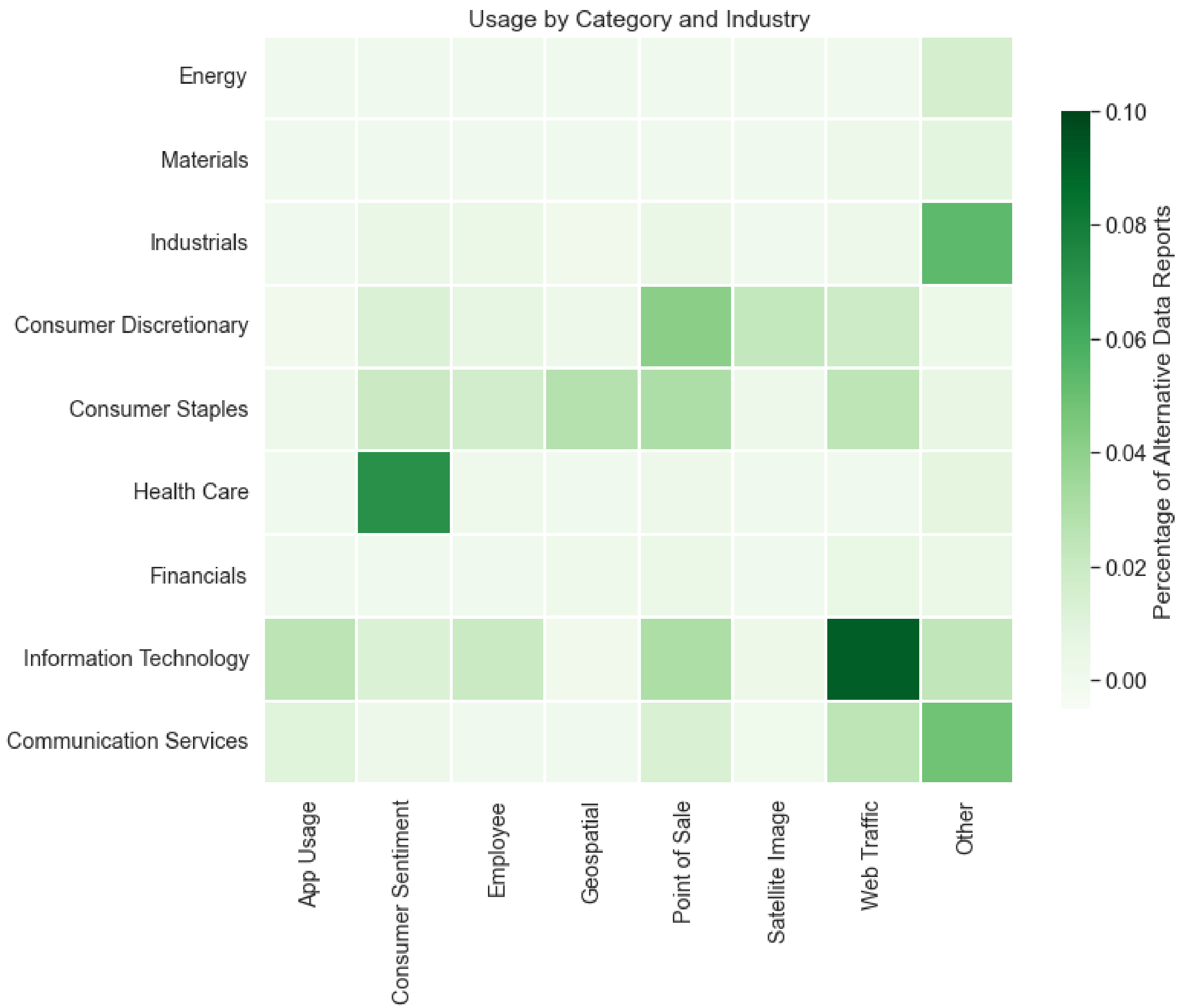


Figure A4
Alternative Data Usefulness by Category and Industry

This figure plots coefficient estimates on *I(Alternative Data)* from Equation (1) across the 8 alternative data categories and 9 GICS 2-digit level industries. Details are described in Table 3. The color intensity of each cell represents the magnitude of the coefficient estimates, which is indicated by the color gradient scale on the right side of the chart. Darker shades indicate larger coefficient estimates, while lighter shades indicate smaller coefficient estimates. Only coefficients that are statistically significant at 10% level are shown here.

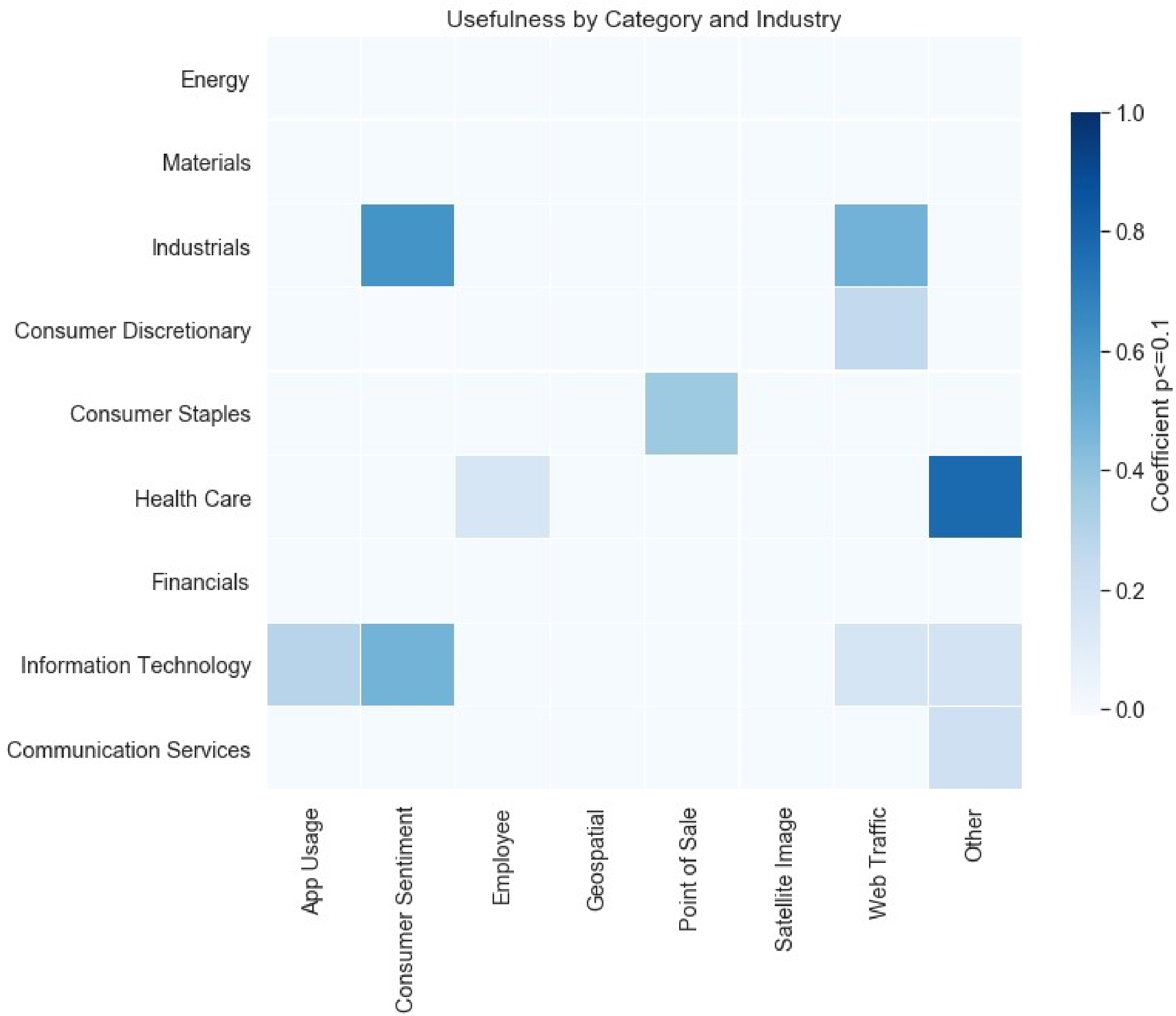


Table A1

Number and Fraction of Firms by Industry: Our Sample versus the CRSP/Compustat Universe

In this table we present the numbers of firms in our sample by Global Industry Classification Standard (GICS) industry sector, the fractions of firms that are in the corresponding GICS industry sectors, the numbers of firms in the CRSP/Compustat universe by GICS industry sector, the fractions of firms that are in the corresponding GICS industry sectors, and the combined market values of the firms in our sample as a percentage of the combined market values of all firms in the CRSP/Compust universe by GICS industry sector. Our sample contains all firms in the Dow Jones Industrial Average Index from June 1 2009 through May 31 2019.

	Our Sample	%	CRSP/Compustat Universe	%	$\sum$ Market Value $_{\text{Our Sample}}$ / $\sum$ Market Value $_{\text{Crsp/Compustat}}$
Energy	2	6%	362	8%	17%
Materials	2	6%	261	5%	9%
Industrials	5	14%	577	12%	17%
Consumer Discretionary	3	9%	519	11%	11%
Consumer Staples	5	14%	166	3%	31%
Health Care	4	11%	882	18%	22%
Financials	5	14%	816	17%	13%
Information Technology	6	17%	632	13%	40%
Communication Services	3	9%	220	5%	16%
Utilities	0	0%	107	2%	0%
Real Estate	0	0%	234	5%	0%

Table A2
How Much Incremental Insight Is There in Alternative Data? Using Absolute Forecast Error

This table replicates Table 3, but the dependent variable is now the absolute forecast error of analyst *i* predicting earnings of firm *j*, scaled by the absolute value of the actual earnings, multiplied by (-1). We report *t*-statistics in parentheses. We double-cluster our standard errors at the analyst- and year-month levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
I(Alternative Data)	0.013***	
	(3.98)	
I(Category = App Usage)		0.020***
		(2.45)
I(Category = Sentiment)		0.011*
		(1.75)
I(Category = Employee)		0.005
		(0.81)
I(Category = Geospatial)		-0.011**
		(-2.50)
I(Category = Point of Sale)		0.004
		(1.48)
I(Category = Satellite Image)		0.008
		(0.73)
I(Category = Web Traffic)		0.014**
		(2.06)
I(Category = Others)		0.016***
		(3.00)
Forecast Age	-0.022***	-0.022***
	(-9.72)	(-9.71)
Analyst/Firm Experience	-0.003	-0.003
	(-0.62)	(-0.65)
Analyst Experience	0.010*	0.010**
	(2.08)	(2.08)
#Firms Covered	0.005	0.005
	(1.17)	(1.15)
Forecast Frequency	0.004	0.003
	(1.55)	(1.51)
Broker Size	-0.000	-0.000*
	(-1.62)	(-1.70)
Analyst-Firm Fixed Effects	Yes	Yes
Firm-Year Fixed Effects	Yes	Yes
N	64,018	64,018
Adjusted R^2	0.822	0.822

Table A3
Summary Statistics

This table reports summary statistics for all variables in our main tests. Appendix 2 defines all variables. All continuous variables are winsorized at the 1% and 99% levels.

Variables	Mean (1)	SD (2)	P25 (3)	P50 (4)	P75 (5)	# of Obs. (6)
Acc	-0.004	0.788	-0.410	0.152	0.603	64,018
I(Alternative Data)	0.088	0.283	0	0	0	64,018
Forecast Age	4.913	1.120	4.575	5.236	5.631	64,018
Analyst/Firm Experience	6.692	6.828	1.784	4.512	9.191	64,018
Analyst Experience	13.874	9.542	5.732	11.937	21.907	64,018
#Firms Covered	2.907	0.370	2.708	2.944	3.135	64,018
Forecast Frequency	6.362	0.679	6.038	6.450	6.819	64,018
Broker Size	87.096	50.219	47	84	116	64,018
Trading Commissions	33,191	59,541	3000	11,578	34,422	4,757
I(In-House Data Science Team)	0.158	0.365	0	0	0	64,018
$\sum$ *Colleagues* $_{Alternative\ Data}$	2.050	2.424	0	1	3	64,018
Number of 8-Ks	15.702	7.310	10	14	21	64,018
Return Volatility	0.012	0.005	0.009	0.011	0.013	64,018
Earnings Surprise	0.001	0.016	-0.002	0.001	0.004	64,018
I(Earnings Restatement)	0.320	0.466	0	0	1	64,018
Discretionary Accruals	0.111	0.151	0.018	0.063	0.141	64,018
I(Lack of Preferential Access to Management)	0.752	0.432	1	1	1	64,018
Size	11.769	0.779	11.217	11.854	12.263	64,018
M/B	4.256	5.503	1.861	2.921	4.484	64,018
Momentum	0.083	0.154	-0.013	0.076	0.177	64,018
I(Category = App Usage)	0.007	0.086	0	0	0	64,018
I(Category = Sentiment)	0.017	0.128	0	0	0	64,018
I(Category = Employee)	0.008	0.092	0	0	0	64,018
I(Category = Geospatial)	0.004	0.063	0	0	0	64,018
I(Category = Point of Sale)	0.017	0.129	0	0	0	64,018
I(Category = Satellite Image)	0.003	0.052	0	0	0	64,018
I(Category = Web Traffic)	0.030	0.172	0	0	0	64,018
I(Category = Others)	0.021	0.142	0	0	0	64,018
$\sum$ *Categories*	0.107	0.375	0	0	0	64,018
I(Source = Proprietary Data)	0.043	0.204	0	0	0	64,018
I(Source = Accessible Data)	0.057	0.231	0	0	0	64,018

Description of Analysis Tabulated in Online Appendix Table A4

An analyst's decision to adopt alternative data may coincide with an analyst's decision to exert greater effort covering the corresponding firm. To assess the relevance of this possibility, we construct measures of analyst effort that have been used in prior literature (Merkley, Michaely, and Pacelli, 2017; Hwang, Liberti, and Sturgess, 2019; Grennan and Michaely, 2020). We then test whether the adoption of alternative data comes with greater effort.

Our regression equation is similar to regression equation (6):

$$Effort_{i,f,t} = \eta_{i,f} + \theta_{f,t} + \beta\, I(Alternative\ Data_{i,f,t}) + \gamma`\, Controls + \varepsilon_{i,f,t} \quad (9)$$

First, for each analyst/firm/year, we compute the number of days between the earnings announcement and the analyst's most recent forecast prior to the corresponding earnings announcement, multiplied by (-1). We also compute the number of forecast revisions made by the corresponding analyst for the corresponding firm's earnings. Analysts who exert greater effort should issue earnings forecasts that are less stale (Merkley, Michaely, and Pacelli, 2017) and, in general, update their earnings forecasts more frequently (Hwang, Liberti, and Sturgess, 2019).

Motivated by Grennan and Michaely (2020), we also construct the following measures based on analysts' earnings conference call behavior. First, we construct an indicator, which equals one if the analyst participated in the earning conference call discussing the corresponding firm's annual earnings and zero otherwise. Within the subset of analysts who participate in an earnings conference call, we also construct: (a) the total number of questions posed by the analyst, (b) the total number of words spoken by the analyst, (c) *Easy-to-measure Earnings Topics*, which, following Grennan and Michaely (2020) equals one if an analyst's questions contain the words "*sale*," "*margin*," "*price*," or "*capital*," and (d) *Hard-to-measure Earnings Topics*, which, following Grennan and Michaely equals one if an analyst's questions contain the words "*adapt*," "*brand*," "*engage*," or "*technology*." We obtain our earnings conference call data through Refinitiv.

We report our findings in Table A4. For our regressions based on analysts' forecasts, we find that the estimates of *I(Alternative Data)* are small in magnitude and not statistically significant. That is, we find that the adoption of alternative data changes neither the timeliness of forecasts nor the number of forecast revisions.

Similarly, for our regressions based on analysts' conference call behavior, we find that the adoption of alternative data changes neither the number of questions asked, nor the number of words spoken, nor the types of questions asked. We do find that adopting alternative data marginally increases the likelihood of attending a conference call; the corresponding estimate of *I(Alternative Data)* is 0.040 (*t*-statistic = 1.67).

Table A4
Alternative Data Adoption and Analyst Effort

This table reports coefficient estimates from regressions of various measures of analyst effort on whether an analyst explicitly references the use of alternative data in her written report. The observations are at the analyst/firm/year level. The regressions are identical to that in column (1) of Table 3, except that the dependent variables are proxies for analyst effort. In column (1), analyst effort is measured by the number of forecast revisions made by the corresponding analyst for the corresponding firm's earnings. In column (2), analyst effort is measured by the number of days between the date of the analyst's last forecast prior to the earnings announcement date and the earnings announcement date, multiplied by (-1). The dependent variables in columns (3) through columns (7) are an indicator if the analyst participated in the earning conference call discussing the corresponding firm's annual earnings, the total number of questions posed by the analyst, the total number of words spoken by the analyst, and whether the analyst's questions pertained to "easy-to-measure earnings topics," or "hard-to-measure earnings topics." We no longer include *Forecast Age* and *Forecast Frequency* as controls. We report *t*-statistics in parentheses. We double-cluster our standard errors at the analyst- and year-month levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Analyst Forecasts and Reports		Conference Call Behavior				
	Number of Forecast Revisions	Timeliness of Forecast	Attendance	Number of Questions Asked	Number of Words Spoken	Easy-to-Measure Topic	Hard-to-Measure Topic
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
I(Alternative Data)	0.059	0.919	0.040*	-0.048	-2.281	-0.074	-0.027
	(0.46)	(0.26)	(1.67)	(-0.31)	(-0.47)	(-1.26)	(-0.99)
Analyst/Firm Experience	0.023	3.296	0.004	0.017	0.743	-0.026	-0.009
	(0.40)	(1.22)	(0.55)	(0.46)	(0.37)	(-1.04)	(-0.73)
Analyst Experience	0.168**	14.549**	0.012*	0.009	6.579**	0.058**	0.007
	(2.60)	(2.19)	(1.67)	(0.13)	(2.60)	(2.25)	(0.40)
#Firms Covered	0.551***	15.555**	0.057	0.317	20.217*	0.024	0.046
	(3.75)	(2.28)	(1.41)	(1.47)	(1.97)	(0.24)	(0.96)
Broker Size	-0.003**	-0.063	0.000	0.003**	0.082	-0.001*	0.001**
	(-1.98)	(-0.81)	(0.40)	(2.22)	(1.22)	(-1.96)	(2.01)
Analyst-Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,831	5,831	5,831	2,007	2,007	2,007	2,007
Adjusted R^2	0.418	0.521	0.475	0.644	0.539	0.095	0.172

Table A5
Alternative Data and Retail Order Imbalance

This table reports coefficient estimates from regressions of cumulative abnormal returns on changes in analyst forecasts. The observations are at the analyst/firm/forecast date level. We remove observations that coincide with quarterly earnings announcements. The dependent variable is retail order imbalance, measured for firm *i* over the first two trading days of the forecast change. We follow Barber, Huang, Jorion, Odean, and Schwarz (2023) to identify and sign retail trades and calculate retail order imbalance as the difference between retail buy volume and retail sell volume, scaled by total retail trading volume. *I(Alternative Data)* is an indicator variable, which equals one if the corresponding analyst's forecast is explicitly supported by alternative data and zero otherwise. In columns (1) and (2), *Δ* is the percentage change in the earnings forecast. In columns (3) and (4), *Δ* is the percentage change in the target price. In columns (5) and (6), we convert recommendations to numerical scores (1 for sell-, 2 for hold-, and 3 for buy recommendations); *Δ* is the change in the numerical score. We define all remaining variables in Appendix 2. "Firm Characteristics Controls" include *Size*, *M/B*, and *Momentum*. We report *t*-statistics in parentheses. We double-cluster our standard errors at the analyst- and year-month levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Earnings Forecast Change	Target Price Change	Recommendation Change
	(1)	(2)	(3)
I(Alternative Data) × Δ	0.055	0.055	0.026**
	(0.38)	(1.06)	(2.38)
Δ	-0.019	0.021	0.008*
	(-0.46)	(1.25)	(1.87)
I(Alternative Data)	0.000	0.001	0.000
	(0.09)	(0.39)	(0.21)
Forecast Age	-0.009**	-0.006**	-0.007**
	(-2.46)	(-2.13)	(-2.38)
Analyst/Firm Experience	-0.001	-0.001	-0.001
	(-1.43)	(-1.37)	(-1.35)
Analyst Experience	0.001	0.000	0.001
	(1.53)	(0.43)	(0.88)
#Firms Covered	0.001	0.002	0.003
	(0.23)	(0.44)	(0.69)
Forecast Frequency	-0.002	-0.003	-0.003
	(-0.84)	(-1.13)	(-1.34)
Broker Size	0.000*	0.000***	0.000**
	(1.67)	(3.10)	(2.17)
Analyst-Firm Fixed Effects	Yes	Yes	Yes
Firm-Year Fixed Effects	Yes	Yes	Yes
N	37,955	34,697	37,848
Adjusted R^2	0.438	0.442	0.436

Table A6
Retail Order Imbalance and Future Returns

This table reports results from Fama and MacBeth (1973) regressions of future returns on retail imbalances and control variables. The independent variable *Imbalance*[0,1] is retail order imbalance, measured for firm *i* over the first two trading days following the analyst report. We follow Barber et al. (2023) to identify and sign retail trades and calculate retail order imbalance as the difference between retail buy volume and retail sell volume, scaled by total retail trading volume. The variable *Ret*[x,y] is the return compounded over days x through y. The variables *Market Equity* and *Book-to-Market* are the logs of market equity from the most recent June and one plus the ratio of book equity from the most recent fiscal year to market equity from the most recent December. We report *t*-statistics in parentheses. Standard errors are based on Newey and West (1987) with 3 lags. *, **, and *** denote significance at 10%, 5%, and 1% levels.

	Alternative Data			Non-alternative Data		
	Ret[2,5]	*Ret*[2,20]	*Ret*[2,60]	*Ret*[2,5]	*Ret*[2,20]	*Ret*[2,60]
Imbalance[0,1]	0.010	0.026*	0.053*	0.005***	0.021**	0.029**
	(1.45)	(2.21)	(2.15)	(3.34)	(2.58)	(2.25)
Ret[0,1]	-0.032**	-0.104	-0.152	-0.033***	-0.076***	-0.115***
	(-2.54)	(-1.51)	(-1.26)	(-3.18)	(-3.44)	(-5.63)
Ret[−5,−1]	-0.061	-0.098	-0.210**	-0.031***	-0.056**	-0.078**
	(-1.61)	(-1.68)	(-2.46)	(-3.92)	(-2.48)	(-2.73)
Ret[−26,−6]	-0.018**	-0.115***	-0.223*	-0.019**	-0.064***	-0.123***
	(-2.72)	(-5.07)	(-2.20)	(-2.47)	(-3.67)	(-4.82)
Market Equity	-0.002	-0.004	-0.004	0.000	-0.003	-0.005
	(-0.89)	(-0.87)	(-0.43)	(-1.03)	(-1.36)	(-1.13)
Book-to-Marke	-0.014**	-0.056***	-0.104***	-0.003	-0.005	-0.013
	(-2.50)	(-4.51)	(-3.22)	(-1.15)	(-0.99)	(-1.04)
Intercept	0.030	0.075	0.115	0.009	0.048*	0.104
	(1.06)	(1.34)	(1.17)	(1.60)	(1.82)	(1.78)
Average R^2	0.061	0.111	0.177	0.016	0.036	0.063
Average *N*	357	357	357	1,870	1,870	1,870

Table A7
Alternative Data and Stock Market Reactions

This table reports coefficient estimates from regressions of cumulative abnormal returns on changes in analyst forecasts. The observations are at the analyst/firm/forecast date level. We remove observations that coincide with quarterly earnings announcements. The dependent variable is the percentage cumulative market-adjusted return in the first two trading days of the forecast change. *I(Alternative Data)* is an indicator variable, which equals one if the corresponding analyst's forecast is explicitly supported by alternative data and zero otherwise. In columns (1) and (2), *Δ* is the percentage change in the earnings forecast. In columns (3) and (4), *Δ* is the percentage change in the target price. In columns (5) and (6), we convert recommendations to numerical scores (1 for sell-, 2 for hold-, and 3 for buy recommendations); *Δ* is the change in the numerical score. We define all remaining variables in Appendix 2. "Firm Characteristics Controls" include *Size*, *M/B*, and *Momentum*. We report *t*-statistics in parentheses. We double-cluster our standard errors at the analyst- and year-month levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Earnings Forecast Change	Target Price Change	Recommendation Change
	(1)	(2)	(3)
I(Alternative Data) × Δ	7.620***	2.567**	0.600**
	(3.26)	(2.51)	(2.13)
Δ	4.231***	2.899***	0.716***
	(4.58)	(6.61)	(8.91)
I(Alternative Data)	0.105***	0.071*	0.104**
	(2.78)	(1.79)	(2.47)
Forecast Age	-0.016	-0.02	-0.016
	(-0.76)	(-0.99)	(-0.81)
Analyst/Firm Experience	-0.021**	-0.023***	-0.021*
	(-2.43)	(-3.52)	(-1.75)
Analyst Experience	0.017	-0.002	0.025
	(0.64)	(-0.08)	(1.21)
#Firms Covered	-0.092	-0.071	-0.085
	(-1.39)	(-1.07)	(-1.37)
Forecast Frequency	0.090**	0.05	0.090**
	(2.47)	(1.43)	(2.40)
Broker Size	-0.001*	-0.001**	-0.001**
	(-1.68)	(-1.98)	(-2.13)
Analyst-Firm Fixed Effects	Yes	Yes	Yes
Firm-Year Fixed Effects	Yes	Yes	Yes
N	37,955	34,697	37,848
Adjusted R^2	0.045	0.046	0.044

Table A8
Variation in the Usefulness of Alternative Data

This table reports results from repeating the analysis tabulated in column (1) of Table 3, but we now conduct the analysis separately on observations for which we predict alternative data are more advantageous (column (1)) and observations for which alternative data are less advantageous (column (2)). In Panels A, B, C, and E, we separately consider observations in the top and the bottom quintile with regards to *Number of 8-Ks*, *Return Volatility*, *Earnings Surprise*, and *Discretionary Accruals*, respectively. In Panel D, we separate observations by whether the corresponding firm has had to restate its financial accounts or not. In Panel F, we separate observations by whether, over the previous year, the corresponding firm participated in a conference hosted by the corresponding analyst's broker or not. We report *t*-statistics in parentheses. We double-cluster our standard errors at the analyst- and year-month levels. We also report the *p*-value from the Wald test comparing coefficients across seemingly unrelated regression models (Zellner, 1962). The Wald test allows us to compare coefficients without the constraint of having to assume equal control variable coefficients across different subsamples.

	Alternative Data …		
	… More Advantageous (1)	… Less Advantageous (2)	Test of Coefficient Equality (*p*-value)
Panel A: Number of 8-Ks ("Bottom Quintile" versus "Top Quintile")			
I(Alternative Data)	0.380***	0.208***	0.137
N	12,638	12,567	
Panel B: Return Volatility ("Top Quintile" versus "Bottom Quintile")			
I(Alternative Data)	0.269***	0.212***	0.548
N	13,101	12,742	
Panel C: Earnings Surprise ("Top Quintile" versus "Bottom Quintile")			
I(Alternative Data)	0.394***	0.102*	0.005
N	12,687	12,777	
Panel D: Earnings Restatement ("Yes" versus "No")			
I(Alternative Data)	0.322***	0.117***	0.003
N	20,477	43,559	
Panel E: Discretionary Accruals ("Top Quintile" versus "Bottom Quintile")			
I(Alternative Data)	0.372***	0.154*	0.112
N	12,728	12,843	
Panel F: Preferential Access to Management ("No" versus "Yes")			
I(Alternative Data)	0.231***	0.139***	0.132
N	48,125	15,911	

Table A9
Alternative Data and Forecast Accuracy Among Small Firms

This table reports results from repeating the analysis tabulated in Table 3, but we now estimate the regressions for small firms. We report *t*-statistics in parentheses. We double-cluster our standard errors at the analyst- and year-month levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)
I(Alternative Data)	0.197*
	(1.81)
Forecast Age	-0.023
	(-0.67)
Analyst/Firm Experience	0.455**
	(2.41)
Analyst Experience	0.801***
	(3.57)
#Firms Covered	-0.024
	(-0.22)
Forecast Frequency	0.041
	(0.79)
Broker Size	0.002
	(0.86)
Analyst-Firm Fixed Effects	Yes
Firm-Year Fixed Effects	Yes
N	13,123
Adjusted R^2	0.335

Table A10
Alternative Data and Trading Commissions Among Small Firms

This table reports results from repeating the analysis tabulated in Table 4, but we now estimate the regressions for small firms. We report *t*-statistics in parentheses. We double-cluster our standard errors at the analyst- and year-month levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)
I(Alternative Data)	2818.229***
	(3.38)
Forecast Age	49.939
	(0.07)
Analyst/Firm Experience	2256.087
	(1.21)
Analyst Experience	-66.307
	(-0.15)
#Firms Covered	4685.441
	(0.55)
Forecast Frequency	-3392.209
	(-0.58)
Broker Size	-680.968
	(-0.95)
Broker-Firm Fixed Effects	Yes
Firm-Year Fixed Effects	Yes
N	423
Adjusted R^2	0.189

Table A11
Instrumental Variable Analysis

This table reports the results from two-stage least squares regression. We use *First Time Use* and *Software Budget* as instruments for *I(Alternative Data)*. *First Time Use* is an indicator variable that equals one when an analyst's colleague, affiliated with the same brokerage and operating in the same city, adopts alternative data for the first time. *Software Budget* refers to the allocated budget for software purchases at the broker-year level, sourced from Aberdeen's Computer Intelligence Technology Database. The dependent variables are *I(Alternative Data)* and *Acc*, respectively. We report *t*-statistics in parentheses. We double-cluster our standard errors at the analyst- and year-month levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
First Time Use	0.069***	
	(6.94)	
Software Budget	0.000**	
	(2.33)	
I(Alternative Data)		1.186***
		(3.19)
Forecast Age	-0.014***	-0.247***
	(-5.50)	(-15.80)
Analyst/Firm Experience	-0.000	0.053***
	(-0.17)	(2.78)
Analyst Experience	0.010*	0.019
	(1.84)	(0.49)
#Firms Covered	-0.001	-0.034
	(-0.04)	(-0.51)
Forecast Frequency	-0.027**	0.085***
	(-2.17)	(2.64)
Broker Size	0.000	-0.000
	(0.79)	(-0.08)
Analyst-Firm Fixed Effects	Yes	Yes
Firm-Year Fixed Effects	Yes	Yes
First-stage *F*-statistic	25.02	
N	57,698	57,698

Table A12
Matching Sample Analysis

This table reports results from repeating the analysis tabulated in Table 3 by using the matching sample approach. We report *t*-statistics in parentheses. We double-cluster our standard errors at the analyst- and year-month levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)
I(Alternative Data)	0.204***
	(3.83)
Forecast Age	-0.290***
	(-10.60)
Analyst/Firm Experience	0.014
	(0.35)
Analyst Experience	0.035
	(0.37)
#Firms Covered	0.100
	(0.60)
Forecast Frequency	0.029
	(0.51)
Broker Size	-0.000
	(-0.28)
Analyst-Firm Fixed Effects	Yes
Firm-Year Fixed Effects	Yes
N	10,576
Adjusted R^2	0.320

Table A13

The Adoption of Alternative Data and Earnings Forecast Accuracy: Predicting Revenues versus Residuals

This table reports coefficient estimates from regressions of forecast accuracy on a dummy variable indicating the use of alternative data. The observations are at the analyst/firm/report-date level. The regressions are identical to those in Table 3 except for that we now measure forecast accuracy with regards to revenue (column (1)) and residual (column (2)) as described in Subsection 4.5. We report *t*-statistics in parentheses. We double-cluster our standard errors at the analyst- and year-month levels. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Revenue Forecast Accuracy (1)	Residual Forecast Accuracy (2)	*F*-Test of Equality in Coefficient Estimate
I(Alternative Data)	0.148**	0.107	7.68***
	(2.15)	(1.49)	
Forecast Age	-0.119***	-0.107***	
	(-4.55)	(-4.85)	
Analyst/Firm Experience	0.032	0.055	
	(0.29)	(0.72)	
Analyst Experience	0.979***	0.756***	
	(4.99)	(4.70)	
#Firms Covered	-0.070	-0.024	
	(-0.73)	(-0.34)	
Forecast Frequency	0.076**	0.020	
	(2.12)	(0.65)	
Broker Size	-0.014	-0.047	
	(-0.22)	(-0.73)	
Analyst-Firm Fixed Effects	Yes	Yes	
Firm-Year Fixed Effects	Yes	Yes	
N	27,661	27,661	
Adjusted R^2	0.336	0.391	