ONLINE APPENDIX to

Exit, Tweets, and Loyalty

By Joshua S. Gans, Avi Goldfarb, and Mara Lederman

Not for publication

Table of Contents

APPENDIX A: TABLES

Table A1: Descriptive Statistics for Response Data

Variable	Obs.	Mean	Std. Dev.	Min	Max
Airline replied	3,477,105	0.2143	0.4103	0	1
Airline replied if tweet to airline handle	2,040,504	0.3612	0.3956	0	1
Frequent flier keyword	3,477,105	0.0539	0.2258	0	1
Airline 30-50% share city	3,477,105	0.0958	0.2943	0	1
Airline >50% share city	3,477,105	0.0367	0.1880	0	1
Probability sentiment is negative	3,477,105	0.3612	0.3956	0	1
Number of followers, 25^{th} -50^{th} percentile	3,477,105	0.2521	0.4342	0	1
Number of followers, 50^{th} -75^{th} percentile	3,477,105	0.2503	0.4332	0	1
Number of followers, 75^{th} -99^{th} percentile	3,477,105	0.2379	0.4258	0	1
Number of followers, over 99^{th} percentile	3,477,105	0.0099	0.0989	0	1
Handle	3,477,105	0.5868	0.4924	0	1
Customer service keyword	3,477,105	0.1041	0.3054	0	1
On time performance keyword	3,477,105	0.1588	0.3655	0	1
American Airlines	3,477,105	0.2842	0.4510	0	1
Alaska Airlines	3,477,105	0.0324	0.1770	0	1
JetBlue	3,477,105	0.1336	0.3402	0	1
Delta Air Lines	3,477,105	0.1433	0.3504	0	1
United Airlines	3,477,105	0.2770	0.4475	0	1

US Airways tweets are omitted as there is no response data to those tweets.

Table A2: Descriptive Statistics for Repeat Tweeter Analysis

Variable	Obs.	Mean	Std. Dev.	Min	Max
All tweeters, first tweet about airline					
Tweeted again to same airline	1,457,945	0.3296	0.4701	0	1
Airline replied	1,457,945	0.1475	0.3547	0	1
Frequent flier keyword	1,457,945	0.0436	0.2041	0	1
Airline 30-50% share city	1,457,945	0.0823	0.2748	0	1
Airline >50% share city	1,457,945	0.0270	0.1622	0	1
Probability sentiment is negative	1,457,945	0.3539	0.3932	0	1
Number of followers, 25th -50th percentile	1,457,945	0.2844	0.4512	0	1
Number of followers, 50th -75th percentile	1,457,945	0.2379	0.4258	0	1
Number of followers, 75th -99th percentile	1,457,945	0.1656	0.3717	0	1
Number of followers, over 99th percentile	1,457,945	0.0050	0.0703	0	1
Handle	1,457,945	0.5038	0.5000	0	1
Customer service keyword	1,457,945	0.1011	0.3015	0	1
On time performance keyword	1,457,945	0.1559	0.3628	0	1
American Airlines	1,457,945	1,457,945	0.2369	0.4252	0
Alaska Airlines	1,457,945	1,457,945	0.0343	0.1821	0
JetBlue	1,457,945	1,457,945	0.1343	0.3410	0
Delta Air Lines	1,457,945	1,457,945	0.1748	0.3798	0
United Airlines	1,457,945	1,457,945	0.2650	0.4413	0
First tweet for 2012 tweets					
Tweeted to same airline in 2013 or 2014	259,299	0.3933	0.4885	0	1
Airline replied	259,299	0.0809	0.2728	0	1
Frequent flier keyword	259,299	0.0409	0.1981	0	1
Airline 30-50% share city	259,299	0.0887	0.2843	0	1
Airline >50% share city	259,299	0.0316	0.1748	0	1
Probability sentiment is negative	259,299	0.3521	0.3919	0	1
Number of followers, 25th -50th percentile	259,299	0.2991	0.4579	0	1
Number of followers, 50th -75th percentile	259,299	0.2360	0.4246	0	1
Number of followers, 75th -99th percentile	259,299	0.1665	0.3726	0	1
Number of followers, over 99th percentile	259,299	0.0046	0.0679	0	1
Handle	259,299	0.3929	0.4884	0	1
Customer service keyword	259,299	0.0935	0.2912	0	1
On time performance keyword	259,299	0.1503	0.3573	0	1
American Airlines	259,299	0.2580	0.4376	0	1
Alaska Airlines	259,299	0.0275	0.1635	0	1
JetBlue	259,299	0.1583	0.3651	0	1
Delta Air Lines	259,299	0.1546	0.3615	0	1
United Airlines	259,299	0.2781	0.4481	0	1

ROBUSTNESS TO LOGGED SPECIFICATION

Table A3
Robustness of Table 5: Tweets and On-Time Performance

	(1)	(2)
	City-level location in profile only	City-level all three location measures
Flights delayed or canceled	0.069***	0.073***
	(0.004)	(0.004)
Airline flights departing that location	0.001	0.001
	(0.009)	(0.009)
Fixed effects	Day-location, Airline-location	Day-location, Airline-location
N	338,754	338,754
R-sq	0.451	0.468

Dependent variable is number of tweets as identified in column headers. Number of tweets and delays use log(variable+1). Airline flights is logged. Unit of observation is the location-airline-day. Location is defined by city. Robust standard errors clustered by airport in parentheses. Airline-location fixed effects are estimated directly. Day-location fixed effects are differenced out using stata's xtreg, fe command. +p<0.10, *p<0.05, **p<0.01, ***p<0.001

Table A4
Robustness of Table 6: Tweets, On-Time Performance, and Market Dominance

	(1)	(2)	(3)
	City-level location in profile only	City-level location in profile only	City-level all three location measures
Flights delayed or canceled	0.061***	0.063***	0.066***
	(0.005)	(0.005)	(0.005)
Flights delayed or canceled x Airline 15-30% share city	0.004		
	(0.007)		
Flights delayed or canceled x Airline 30-50% share city	0.025**	0.023**	0.026***
	(0.007)	(0.007)	(0.007)
Flights delayed or canceled x Airline >50% share city	0.062***	0.061***	0.068***
	(0.017)	(0.017)	(0.017)
Airline flights departing that airport	0.001	0.001	0.001
	(0.009)	(0.009)	(0.009)
Fixed effects	Day-location, Airline-location	Day-location, Airline-location	Day-location, Airline-location
N	338,754	338,754	338,754
R-sq	0.451	0.451	0.468

Dependent variable is number of tweets as identified in column headers. Number of tweets and delays use log(variable+1). Airline flights is logged. Unit of observation is the location-airline-day. Location is defined by city. Robust standard errors clustered by airport in parentheses. Airline-location fixed effects are estimated directly. Day-location fixed effects are differenced out using stata's xtreg, fe command. +p<0.10, *p<0.05, **p<0.01, ***p<0.001

Table A5
Robustness of Table 7: On-Time Performance Mentioned in Tweet

	(1)	(2)	(3)	(4)
	Number tweets about on-time performance	Number tweets not about on-time performance	Number tweets about on-time performance	Number tweets not about on-time performance
Flights delayed or canceled	0.071***	0.047***	0.059***	0.042***
	(0.007)	(0.004)	(0.006)	(0.004)
Flights delayed or canceled x Airline 30-50% share city			0.044**	0.019**
			(0.014)	(0.006)
Flights delayed or canceled x Airline >50% share city			0.112**	0.053***
			(0.033)	(0.013)
Airline flights departing that airport	-0.020***	0.007	-0.021***	0.006
	(0.004)	(0.008)	(0.004)	(0.008)
Fixed effects	Day-location, Airline-location	Day-location, Airline-location	Day-location, Airline-location	Day-location, Airline-location
N	338,754	338,754	338,754	338,754
R-sq	0.357	0.442	0.359	0.443

Dependent variable type identified in column headers. Number of tweets and delays use log(variable+1). Airline flights is logged. Unit of observation is the location-airline-day. Location is defined by city. Robust standard errors clustered by airport in parentheses. Airline-location fixed effects are estimated directly. Day-location fixed effects are differenced out using stata's xtreg, fe command. +p<0.10, *p<0.05, **p<0.01, ***p<0.001

Table A6
Robustness of Table 8: Sentiment

	(1)	(2)	(3)	(4)	(5)	(6)
	Average negative sentiment	Average negative sentiment	Number of very negative tweets	Number of very positive tweets	Number of very negative tweets	Number of very positive tweets
Flights delayed or canceled	0.026***	0.027***	0.070***	0.024***	0.060***	0.019***
	(0.002)	(0.002)	(0.007)	(0.002)	(0.006)	(0.003)
Flights delayed or canceled x Airline 30-50% share city		-0.001			0.038**	0.019**
		(0.003)			(0.012)	(0.006)
Flights delayed or canceled x Airline >50% share city		-0.007+			0.100**	0.054***
		(0.004)			(0.030)	(0.011)
Airline flights departing that airport	-0.010*	-0.010*	-0.017***	0.011	-0.018***	0.011
	(0.005)	(0.005)	(0.005)	(0.007)	(0.005)	(0.007)
Fixed effects	Day-location, Airline-location	Day-location, Airline-location	Day-location, Airline-location	Day-location, Airline-location	Day-location, Airline-location	Day-location, Airline-location
N	178,908	178,908	338,754	338,754	338,754	338,754
R-sq	0.079	0.079	0.371	0.419	0.372	0.420

Dependent variable type identified in column headers. Number of tweets and delays use log(variable+1). Airline flights is logged. Unit of observation is the location-airline-day. Location is defined by city. Robust standard errors clustered by airport in parentheses. Airline-location fixed effects are estimated directly. Day-location fixed effects are differenced out using stata's xtreg, fe command. +p<0.10, *p<0.05, **p<0.01, ***p<0.001

Table A7
Robustness of Table 9
Weather, Delay Cause, and the Relationship between On-Time Performance, Tweet Volume and Market Dominance

	(1)	(2)	(2)
Dependent Variable	# tweets	# tweets	# tweets
# flights delayed or canceled	0.063***	0.063***	
	(0.005)	(0.005)	
# flights delayed >15 min or canceled × 30-50% share	0.020**	0.022**	
	(0.008)	(0.008)	
# flights delayed >15 min or canceled × >50% share	0.056**	0.055**	
	(0.018)	(0.018)	
Rain, Snow, or Fog Dummy × 30-50% share	0.013		
	(0.008)		
Rain, Snow, or Fog Dummy × >50% share	0.004		
	(0.012)		
Quantity of Precipitation × 30-50% share		-0.012	
		(0.007)	
Quantity of Precipitation × >50% share		0.020	
		(0.019)	
# flights delayed > 15 min that are airline's fault			0.058***
			(0.004)
# flights delayed > 15 min that are airline's fault × 30-50% share			0.014
			(0.009)
# flights delayed >15 min that are airline's fault × >50% share			0.036*
			(0.018)
# flights delayed > 15 min that are *not airline's fault*			0.047***
			(0.005)
# flights delayed > 15 min that are *not* airline's fault × 30-50% share			-0.005
			(0.008)
# flights delayed >15 min that are *not* airline's fault × >50% share			0.001
			(0.015)
# airline flights departing that airport	0.0001	0.0001	0.010
	(0.009)	(0.009)	(0.012)
Fixed effects	Day-location	Day-location	Day-location
N	312,011	308,715	229,984
R-sq	0.435	0.435	0.429

Dependent variable is number of tweets with city-location known. Number of tweets and delays use log(variable+1). Airline flights is logged. Unit of observation is the location-airline-day. Location is defined by city. Robust standard errors clustered by airport in parentheses. Airline-location fixed effects are estimated directly. Day-location fixed effects are differenced out using stata's xtreg, fe command. +p<0.10, *p<0.05, **p<0.01, ***p<0.001

Table A8
Robustness of Table 11: Handles

	(1)	(2)	(3)	(4)
	Number tweets to handle	Number tweets not to handle	Number tweets to handle	Number tweets not to handle
Flights delayed or canceled	0.065***	0.030***	0.057***	0.027***
	(0.005)	(0.003)	(0.005)	(0.003)
Flights delayed or canceled x Airline 30-50% share city			0.028***	0.006
			(0.007)	(0.006)
Flights delayed or canceled x Airline >50% share city			0.077***	0.038**
			(0.019)	(0.014)
Airline flights departing that airport	-0.004	0.002	-0.004	0.001
	(0.008)	(0.007)	(0.008)	(0.007)
Fixed effects	Day-location, Airline-location	Day-location, Airline-location	Day-location, Airline-location	Day-location, Airline-location
N	338,754	338,754	338,754	338,754
R-sq	0.452	0.320	0.452	0.320

Dependent variable type identified in column headers. Number of tweets and delays use log(variable+1). Airline flights is logged. Unit of observation is the location-airline-day. Location is defined by city. Robust standard errors clustered by airport in parentheses. Airline-location fixed effects are estimated directly. Day-location fixed effects are differenced out using stata's xtreg, fe command. +p<0.10, *p<0.05, **p<0.01, ***p<0.001

Table A9
Robustness of Table 12
Relationship between On-Time Performance, Market Dominance, and Average Number of Followers

	(1)	(2)
Dependent Variable	Average # of followers	Average # of followers
# flights delayed or canceled	0.023*	0.019*
	(0.009)	(0.009)
# flights delayed >15 min or canceled × 30-50% share		0.022
		(0.024)
# flights delayed >15 min or canceled × >50% share		0.029
		(0.028)
# airline flights departing that airport	-0.021	-0.021
	(0.038)	(0.039)
Fixed effects	Day-location, Airline-location	Day-location, Airline-location
N	178,810	178,810
R-sq	0.059	0.059

Dependent variable is in column headers with city-level tweets with the location in profile known. Number of delays and average number of followers use log(variable+1). Airline flights is logged. Unit of observation is the location-airline-day. Location is defined by city. Robust standard errors clustered by airport in parentheses. Airline-location fixed effects are estimated directly. Day-location fixed effects are differenced out using stata's xtreg, fe command. +p<0.10, *p<0.05, **p<0.01, ***p<0.001

ROBUSTNESS TO AIRPORT LEVEL SPECIFICATION

Table A10

Robustness of Table 5: Tweets and On-Time Performance

	(1)	(2)	(3)	(4)
Dependent Variable	Standardized # Tweets	Standardized # Tweets	Standardized # Tweets	Standardized # Tweets
Location Measure	Closest airport	Airport in tweet	Both Airport-level location measures	Within two miles of airport
Flights delayed or canceled	0.052***	0.066***	0.073***	0.046***
	(0.004)	(0.004)	(0.004)	(0.004)
Airline flights departing that location	-0.0001	0.002	0.002	0.006+
	(0.003)	(0.003)	(0.003)	(0.003)
Fixed effects	Day-location	Day-location	Day-location	Day-location
N	382,141	382,141	382,141	371,883
R-sq	0.002	0.003	0.004	0.002

Dependent variable is number of tweets as identified in column headers. All variables are normalized using airline-airport mean and standard deviation. Location is defined by airport. Robust standard errors clustered by airport in parentheses. Day-location fixed effects are differenced out using stata's xtreg, fe command. +p<0.10, *p<0.05, **p<0.01, ***p<0.001

Table A11
Robustness of Table 6: Tweets, On-Time Performance, and Market Dominance

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Standardized # Tweets	Standardized # Tweets	Standardized # Tweets	Standardized # Tweets	Standardized # Tweets
Location Measure	Closest airport	Closest airport	Airport in tweet	Both Airport-level location measures	Within two miles of airport
Flights delayed or canceled	0.039***	0.044***	0.055***	0.062***	0.039***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Flights delayed or canceled	0.012+				
x Airline 15-30% share city	(0.006)				
Flights delayed or canceled	0.045***	0.040***	0.049***	0.051***	0.030**
x Airline 30-50% share city	(0.009)	(0.009)	(0.011)	(0.009)	(0.010)
Flights delayed or canceled	0.100***	0.097***	0.135***	0.136***	0.091***
x Airline >50% share city	(0.018)	(0.019)	(0.023)	(0.023)	(0.019)
Airline flights departing	-0.001	-0.001	0.001	0.001	0.005+
that airport	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Fixed effects	Day-location	Day-location	Day-location	Day-location	Day-location
N	382,141	382,141	382,141	382,141	371,883
R-sq	0.003	0.003	0.004	0.005	0.002

Dependent variable is number of tweets as identified in column headers. All variables are normalized using airline-airport mean and standard deviation. Location is defined by airport. Robust standard errors clustered by airport in parentheses. Day-location fixed effects are differenced out using stata's xtreg, fe command.
+p<0.10, *p<0.05, **p<0.01, ***p<0.001

Table A12
Robustness of Table 7: On-Time Performance Mentioned in Tweet

	(1)	(2)	(3)	(4)
	Standardized Number tweets about on-time performance	Standardized Number tweets not about on-time performance	Standardized Number tweets about on-time performance	Standardized Number tweets not about on-time performance
Flights delayed or canceled	0.064***	0.034***	0.056***	0.028***
	(0.005)	(0.003)	(0.004)	(0.003)
Flights delayed or canceled x Airline 30-50% share city			0.040***	0.031***
			(0.011)	(0.008)
Flights delayed or canceled x Airline >50% share city			0.108***	0.077***
			(0.020)	(0.018)
Airline flights departing that airport	-0.004	0.001	-0.005+	0.001
	(0.002)	(0.003)	(0.002)	(0.003)
Fixed effects	Day-location	Day-location	Day-location	Day-location
N	380,637	382,141	380,637	382,141
R-sq	0.003	0.001	0.003	0.001

Dependent variable is number of tweets as identified in column headers. All variables are normalized using airline-airport mean and standard deviation. Location is defined by airport. Robust standard errors clustered by airport in parentheses. Day-location fixed effects are differenced out using stata's xtreg, fe command. +p<0.10, *p<0.05, **p<0.01, ***p<0.001

Table A13
Robustness of Table 8: Sentiment

	(1)	(2)	(3)	(4)	(5)	(6)
	Standardized Average negative sentiment	Standardized Average negative sentiment	Standardized Number of very negative tweets	Standardized Number of very positive tweets	Standardized Number of very negative tweets	Standardized Number of very positive tweets
Flights delayed or canceled	0.085***	0.079***	0.063***	0.014***	0.055***	0.009***
	(0.007)	(0.007)	(0.004)	(0.003)	(0.004)	(0.003)
Flights delayed or canceled x Airline 30-50% share city		0.036*			0.037**	0.021**
		(0.015)			(0.011)	(0.007)
Flights delayed or canceled x Airline >50% share city		0.005			0.104***	0.053***
		(0.014)			(0.019)	(0.015)
Airline flights departing that airport	-0.027***	-0.028***	-0.008**	0.006*	-0.008***	0.006*
	(0.007)	(0.007)	(0.002)	(0.003)	(0.002)	(0.003)
Fixed effects	Day-location	Day-location	Day-location	Day-location	Day-location	Day-location
N	88,807	88,807	379,590	382,141	379,590	382,141
R-sq	0.004	0.004	0.003	0.0001	0.003	0.0001

Dependent variable is number of tweets as identified in column headers. All variables are normalized using airline-airport mean and standard deviation. Location is defined by airport. Robust standard errors clustered by airport in parentheses. Day-location fixed effects are differenced out using stata's xtreg, fe command. +p<0.10, *p<0.05, **p<0.01, ***p<0.001

Table A14

Robustness of Table 9: Weather, Delay Cause, and the Relationship between On-Time Performance, Tweet Volume and Market Dominance

	(1)	(2)	(2)
Dependent Variable	Standardized # tweets	Standardized # tweets	Standardized # tweets
# flights delayed or canceled	0.045***	0.044***	
	(0.004)	(0.004)	
# flights delayed >15 min or canceled × 30-50% share	0.041***	0.041***	
	(0.009)	(0.009)	
# flights delayed >15 min or canceled × >50% share	0.090***	0.094***	
	(0.020)	(0.020)	
Rain, Snow, or Fog Dummy × 30-50% share	0.0005		
	(0.005)		
Rain, Snow, or Fog Dummy × >50% share	0.004		
	(0.009)		
Quantity of Precipitation × 30-50% share		-0.005	
		(0.005)	
Quantity of Precipitation × >50% share		-0.013	
		(0.009)	
# flights delayed > 15 min that are airline's fault			0.040***
			(0.004)
# flights delayed > 15 min that are airline's fault × 30-50% share			0.017*
			(0.008)
# flights delayed >15 min that are airline's fault × >50% share			0.069***
			(0.016)
# flights delayed > 15 min that are *not airline's fault*			0.018***
			(0.004)
# flights delayed > 15 min that are *not* airline's fault × 30-50% share			0.017*
			(0.008)
# flights delayed >15 min that are *not* airline's fault × >50% share			0.026*
			(0.011)
# airline flights departing that airport	-0.001	-0.001	0.001
	(0.003)	(0.003)	(0.004)
Fixed effects	Day-location	Day-location	Day-location
N	352,415	348,881	260,442
R-sq	0.003	0.003	0.003

Dependent variable is airport-level tweets with goecode. Airline fault is defined by the airline in regulatory filings. All variables are normalized using airline-location mean and standard deviation. Unit of observation is the location-airline-day. Location is defined by airport. Robust standard errors clustered by airport in parentheses. Day-location fixed effects are differenced out using stata's xtreg, fe command. +p<0.10, *p<0.05, **p<0.01, ***p<0.001

Table A15
Robustness of Table 11: Handles

	(1)	(2)	(3)	(4)
	Standardized Number tweets to handle	Standardized Number tweets not to handle	Standardized Number tweets to handle	Standardized Number tweets not to handle
Flights delayed or canceled	0.050***	0.024***	0.042***	0.020***
	(0.004)	(0.003)	(0.003)	(0.003)
Flights delayed or canceled x Airline 30-50% share city			0.043***	0.016+
			(0.009)	(0.008)
Flights delayed or canceled x Airline >50% share city			0.089***	0.068***
			(0.018)	(0.016)
Airline flights departing that airport	-0.002	0.005+	-0.003	0.005+
	(0.002)	(0.003)	(0.002)	(0.003)
Fixed effects	Day-location	Day-location	Day-location	Day-location
N	382,141	382,141	382,141	382,141
R-sq	0.002	0.0001	0.002	0.001

Dependent variable is number of tweets as identified in column headers. All variables are normalized using airline-location mean and standard deviation. Location is defined by airport. Robust standard errors clustered by airport in parentheses. Airline-location fixed effects are estimated directly. Day-location fixed effects are differenced out using stata's xtreg, fe command. +p<0.10, *p<0.05, **p<0.01, ***p<0.001

Table A6

Robustness of Table 12: Relationship between On-Time Performance, Market Dominance, and Average Number of Followers

	(1)	(2)
Dependent Variable	Standardized Average # of followers	Standardized Average # of followers
# flights delayed or canceled	0.001	-0.001
	(0.008)	(0.008)
# flights delayed >15 min or canceled × 30-50% share		0.011
		(0.009)
# flights delayed >15 min or canceled × >50% share		0.007
		(0.015)
# airline flights departing that airport	-0.005	-0.005
	(0.005)	(0.005)
Fixed effects	Day-location	Day-location
N	88,807	88,807
R-sq	0.0001	0.0001

Dependent variable is airport-level tweets with goecode. All variables are normalized using airline-location mean and standard deviation. Unit of observation is the location-airline-day. Location is defined by airport. Robust standard errors clustered by airport in parentheses. Day-location fixed effects are differenced out using stata's xtreg, fe command. +p<0.10, *p<0.05, **p<0.01, ***p<0.001

APPENDIX B: EXTENSIONS TO THE THEORY

The model in the paper is geared towards a mass market industry like airlines. When a consumer leaves a firm, they do not expect the prices they face at other firms to change. In addition, the model does not fully model equilibrium outcomes. Here we amend the baseline model on both of these dimensions to demonstrate the robustness of the model's conclusions.

When exit raises price

Here we consider a situation where, if a consumer exits, it has one less firm it can deal with. Suppose that all firms understand this and so they can set prices to this consumer differently. Then, an exiting consumer will face a higher price from other firms.

To illustrate this, consider a Salop circle model with per unit transportation cost of t. Suppose that if a consumer exits a firm, they face a smaller circle with n – 1 firms evenly spaced. Thus, the price they face changes from $c + sB + \frac{t}{n}$ to $c + sB + \frac{t}{n-1}$.[1]

With this, should it exit, the total costs for the consumer if they stay with the firm (LHS of B1 below) is that they face the same price (because the other consumers with that firm are presumably still under the assumption that there is a relational contract) while if they exit (RHS of B1 below), the price goes up but the consumer believes that if there is a complaint, they will get mitigation. The costs of staying are higher than those of exit if:

$$c + sB + \frac{t}{n} \geq c + sB + \frac{t}{n-1} - s(B - C) \qquad \text{(B1)}$$

$$\Longrightarrow B \geq C + \frac{t}{sn(n-1)} \qquad \text{(B2)}$$

As n gets large, B2 will hold. For $n = 2$, $B \geq C + \frac{t}{2s}$. Notice that this constraint varies with n in the opposite direction as the firm incentive constraint. This captures the other part of the Hirschman intuition.

Given this, the full condition (that is, (*) in the paper's model) becomes:

$$\frac{\delta}{1-\delta}\frac{t}{n} \geq C + \frac{t}{sn(n-1)}$$

or

$$\frac{\delta st(n-1) - t(1-\delta)}{sn(n-1)(1-\delta)} \geq C$$

[1] In a more realistic setting, the fact that a consumer is at a particular firm means that it will have a further distance from other firms if it exits and, if other firms understood that, the pricing outcome may be different. This is an interesting possibility but involves unnecessary complications for our purposes here, so we make the simplifying 'shrinkage' assumption instead

It can be shown that this constraint is more likely to hold as n falls so the comparative static we have emphasized still holds. That is despite consumers facing increased prices if they exit, the relative costs of exit rise faster for firms.

Full Equilibrium Model

We now provide a model based on our baseline model (without exit-associated price changes) that will give us $p(n, B)$ as an equilibrium outcome. Suppose that the n firms compete a la Cournot with homogeneous goods. Suppose that the relational contract is in place (where each firm agrees to pay *B* should a consumer communicate a quality decline). Then $p = a - s\Delta + s(B - C) - bQ$ where Q is industry output. In this case, under a Cournot equilibrium it can be shown that:

$$p(n, B) = \frac{a + cn + s(B(n+1) - C - \Delta)}{n+1}$$

Note that as *B* is a pure transfer, it does not impact on prices nor profits. Given (*) in the paper, this means that a relational contract equilibrium will hold if:

$$\delta\left(\frac{a + c - s\Delta}{(n+1)(1-\delta) - \delta s}\right) \geq C$$

As expected as *n* increases, the left hand side of this inequality falls.

Note that allowing voice strictly reduces welfare. Prices are higher but consumer surplus is lower as are profits. The reason is that mitigation (*B*) is a transfer while communication cost (*C*) is a cost. For there to be welfare improvements, the firm must actually be induced to do something of value.

Given this, what we need to check is whether the firm has a long-term incentive to keep to the relational contract. That is, this analysis checks if the firm is willing to honor a relational contract with individual customers but is it willing to honor it with all of them? Suppose that a firm decides to deviate and publicly promise not to respond to complaints while the remaining $n - 1$ firms continue to uphold the relational contract. In this case, the deviating firm ends up with an equilibrium price of:

$$\tilde{p} = \frac{a + cn + s(C(n-1) - \Delta)}{n+1}$$

while the remaining firms end up with an equilibrium price of:

$$p(n, B) = \frac{a + cn + s(B(1+n) - 2C - \Delta)}{n+1}$$

Note that $\tilde{p} < p(n, B) \Rightarrow C < B$. Let's now compare the profits of the deviating firm to its profits in the full relational contracting equilibrium. The profits from deviating will be lower if:

$$B \geq \frac{n}{n+1} C\left(2 - \frac{nsC}{a - c + s((n-1)C - \Delta)}\right)$$

For *n* large, this becomes $C \leq B$ while for $n = 2$, this becomes:

$$B \geq \frac{4}{3}\left(\frac{a-c-s\Delta}{a-c+s(C-\Delta)}\right)C$$

If $B = C$, then this becomes:

$$\frac{a-c-s\Delta+s(n-1)C}{2(a-c-s\Delta)+s(n-2)C} \geq \frac{n}{n+1}$$

For n low, this holds but for n very large it does not hold.

In summary, for n low, it is not worthwhile for a firm to deviate and refuse to acknowledge voice.