Online Appendix for - Cooking or Clicking: The Impact of Online Food Delivery Platforms on Domestic Food Preparation

(Online Appendix for Management Science manuscript no: MS-INS-2023-02636)

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Table A1. Survey weighted means (with SDR linearized SEs) of key variables of individual ATUS microdata for subsampled population reporting cooking times over 2005-19 over 230 US counties, N = 86,691 and population size = 118,974,989.

Variable	Mean	Std. Dev.
CookingTime (Mins)	60.98	59.4
GrubhubAgg (1/0)	0.16	0.37
GrubhubDel (1/0)	0.06	0.25
Age (years)	47.55	17.72
Female (1/0)	0.63	0.48
FamIncome (1000's USD)	69.05	54.41
HHSize	2.95	1.56
HHNumKids	0.78	1.15

This table is comparable to Table 1 in the main manuscript which reports unweighted summary statistics.

Table A2. Correlations for Cooking Times in ATUS, 2005-2019 for all 230 counties in the sample.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) CookingTime (Mins)	1.00						
(2) GrubhubAgg (1/0)	0.02*	1.00					
(3) GrubhubDel (1/0)	0.01*	0.56*	1.00				
(4) Age (years)	0.09*	0.02*	0.02*	1.00			
(5) Female (1/0)	0.24*	-0.00	-0.00	0.05*	1.00		
(6) FamIncome (1000's) USD	-0.03*	0.07*	0.05*	-0.12*	-0.08*	1.00	
(7) HHSize	0.07*	-0.02*	-0.02*	-0.47*	-0.03*	0.24*	1.00

* shows significance at the 0.05 level

Table A3. Impact of Grubhub on the propensity to report any cooking activity among respondents from 2005-2019 in counties with a population >= 100K, eventually receiving at least GrubhubAgg.

DV = AnyCooking [0/1]	(1) County Clustered SEs	(2) SDR Clustered SEs 160 Replications
GrubhubAgg	-0.017	-0.017
	(0.017)	(0.015)
GrubhubDel	0.025	0.025
	(0.019)	(0.019)
FamInc (1000's)	-0.000	-0.000
	(0.000)	(0.000)
HHSize	-0.017***	-0.017***
	(0.005)	(0.004)
HHNumKids	0.055***	0.055***
	(0.006)	(0.006)
Female	0.257***	0.257***
	(0.008)	(0.007)
Age(yrs)	0.005***	0.005***
	(0.000)	(0.000)
Not In Workforce	-0.013	-0.013+
	(0.010)	(0.008)
Unemployed	0.054***	0.054***
	(0.015)	(0.014)
Unemployment(%)	0.001	0.001
	(0.004)	(0.004)
Log(Population)	0.012	0.012
	(0.209)	(0.259)
Log(F&BCnt)	0.191*	0.191
	(0.089)	(0.118)
Fixed Effects	Race, County, State * Year	
N	40,127	40,127
Population Size	-	59,426,785
R^2	0.130	0.130

SEs in parentheses $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Variable	Nobs.	Min	Max	Mean	SD
AnyCooking	40,127	0	1	0.57	0.49

Figure A1. Comparison of demographics between ATUS panels from Table 2.

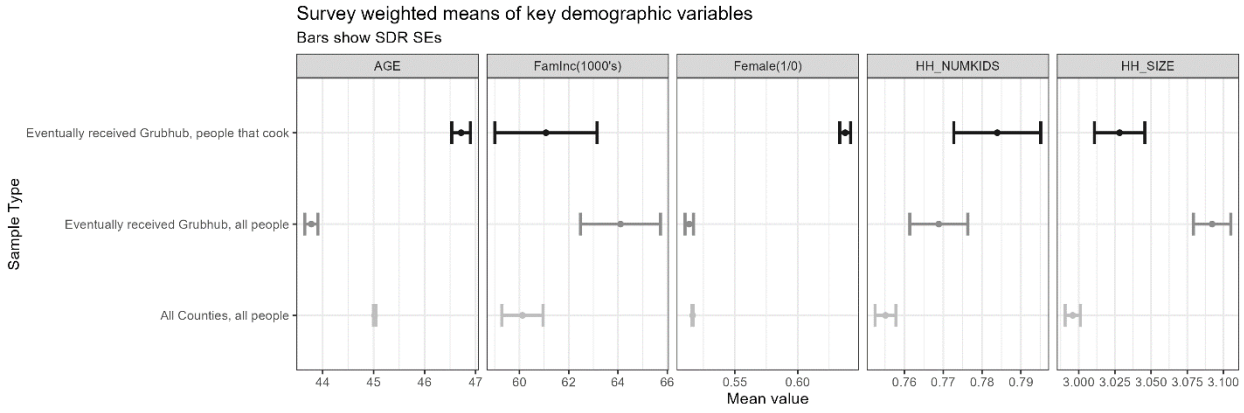

Table A4. Summary statistics for other reported activities in ATUS, 2005-2019 for potentially treated with GrubhubAgg counties.

Activity duration, when respondent engaged in the activity	Nobs.	Min	Max	Mean	SD
Eating Duration (Mins)	41,502	1	1320	72.25	52.52
Eating at Restaurants Duration (Mins)	8,500	1	765	72.64	49.93
Socializing Duration (Mins)	15,203	1	944	113.74	113.30
Watching TV Duration (Mins)	34,320	1	1313	216.57	173.23

Activity duration, when respondent reported cooking at least once.	Nobs.	Min	Max	Mean	SD
Morning Cooking Duration (Mins)	23,060	0	770	18.43	34.92
Midday Cooking Duration (Mins)	23,060	0	745	13.4	32.39
Evening Cooking Duration (Mins)	23,060	0	470	32.99	38.07

Table A5. Heterogeneity in Impact of Grubhub on Cooking Time (mins)

DV = CookingTimes (mins)	(1)	(2)	(3)	(4)	(5)
GrubhubAgg	1.077	1.077	0.798	0.167	-0.178
	(2.126)	(2.126)	(2.073)	(2.177)	(2.237)
GrubhubDelivery	-7.831***	-7.831***	-16.442***	21.794+	7.062
	(2.135)	(2.135)	(4.083)	(11.207)	(13.584)
FamInc (1000's)	-0.062***	-0.062***	-0.061***	-0.061***	-0.062***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
HHSize	6.298***	6.298***	6.297***	6.262***	6.314***
	(0.684)	(0.684)	(0.685)	(0.681)	(0.686)
HHNumKids	1.424	1.424	2.103*	2.159*	1.428
	(0.905)	(0.905)	(0.842)	(0.837)	(0.907)
Female	19.613***	19.613***	19.578***	19.531***	19.556***
	(1.611)	(1.611)	(1.619)	(1.618)	(1.611)
Age(years)	0.363***	0.363***	0.364***	0.362***	0.362***
	(0.043)	(0.043)	(0.044)	(0.043)	(0.043)
Unemployment (%)	-0.696	-0.696	-0.636	-1.058+	-0.926
	(0.584)	(0.584)	(0.588)	(0.584)	(0.595)
Log(Population)	-5.047	-5.047	7.638	-28.741	-15.377
	(18.813)	(18.813)	(18.202)	(18.947)	(19.229)
Log(FBCounts)	1.414	1.414	3.884	8.066	8.868
	(15.001)	(15.001)	(15.426)	(16.008)	(16.316)
GrubhubDelivery*	3.120*	3.120*			2.955*
HHNumKids	(1.377)	(1.377)			(1.373)
GrubhubDelivery*			1.945**		1.298+
Unemployment(%)			(0.647)		(0.705)
GrubhubDelivery*				-3.323*	-2.657+
Log(FBCounts)				(1.303)	(1.344)
Fixed Effects	Race, County, State*Year, EmpState				
N	23,061	23,061	23,061	23,061	23,061
R^2	0.136	0.136	0.136	0.136	0.137

Clustered (by County) SEs in parentheses ,+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A6. Impact of Grubhub Proxies on Cooking Times (mins)

DV = CookingTime (mins)	BaseModel (1)	GTrends 1 (2)	GTrends 2 (3)	GTrends 3 (4)	GHCnt (5)
GrubhubAgg	1.32	1.64	-0.79		-1.75
	(2.08)	(2.20)	(2.55)		(2.82)
GrubhubDel	-5.68**	-6.28**	-3.13		
	(1.95)	(2.03)	(4.46)		
Age (yrs)	0.36***	0.36***	0.36***	0.36***	0.34***
	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
Female	19.59***	20.17***	20.19***	20.18***	21.05***
	(1.62)	(1.67)	(1.67)	(1.67)	(1.71)
FamInc (1000's)	-0.06***	-0.06***	-0.06***	-0.06***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
HHSize	6.27***	6.40***	6.39***	6.39***	5.69***
	(0.68)	(0.70)	(0.70)	(0.70)	(0.64)
HHNumkids	2.16*	1.96*	1.96*	1.95*	1.99*
	(0.84)	(0.86)	(0.86)	(0.86)	(0.96)
Not In Workforce	16.31***	16.51***	16.53***	16.54***	17.00***
	(1.24)	(1.34)	(1.34)	(1.34)	(1.38)
Unemployed	19.10***	19.78***	19.78***	19.76***	18.57***
	(2.10)	(2.13)	(2.14)	(2.13)	(2.24)
Log(Population)	-5.15	4.86	7.68	6.00	-1.69
	(18.85)	(17.44)	(17.93)	(17.98)	(23.96)
Log(FBCount)	1.07	1.79	-4.07	-4.22	1.71
	(15.04)	(15.16)	(15.49)	(15.50)	(17.51)
Unemployment(%)	-0.71	-0.54	-0.45	-0.38	-0.51
	(0.58)	(0.59)	(0.63)	(0.61)	(0.85)
Gtrends (DoorDash)		-0.20	-0.29	-0.26	
		(0.72)	(0.72)	(0.73)	
Gtrends (Grubhub)		-0.43	-3.46	-2.56	
		(0.49)	(2.17)	(1.91)	
GrubhubAgg *Gtrends(Grubhub)			3.15	2.36	
			(1.95)	(1.76)	
GrubhubDel * Gtrends(Grubhub)			-0.48	-0.74***	
			(0.43)	(0.19)	
GrubhubDel * Log ($GHRestCnt_{2015}$)					-1.05***
					(0.23)
Fixed Effects			County, State*Year, Race		
Num. obs.	23,061	21,448	21,448	21,448	19,463
Adj. R^2 (full model)	0.12	0.12	0.12	0.12	0.11
Adj. R^2 (proj model)	0.10	0.10	0.10	0.10	0.10

***p < 0.001; **p < 0.01; *p < 0.05; +p < 0.1, SEs in parentheses clustered by geography

Note: Model (3) the completely specified interaction model shows a high VIF factor > 20 and is thus presented only for completeness and is likely not reliable. In the text only models (2), (4) and (5) are referred to.

Descriptive Statistics for Grubhub Proxies

Variable	Mean	SD	Min	Max
Grubhub(Gtrends)	3.01	4.44	0.00	17.50
DoorDash(Gtrends)	1.49	3.80	0.00	18.58
GHRestCnt(2015)	3,927.05	5,245.54	13	14,826

Table A7. Impact of Grubhub delivery relative to year of platform entry per geography.

	(1) DV = CookingTime (mins)	(2) DV=log(BMI)
RtYear-6	-2.83	0.009*
	(3.82)	(0.004)
RtYear-5	4.66	0.006
	(4.40)	(0.004)
RtYear-4	-1.24	-0.004
	(3.35)	(0.003)
RtYear-3	-0.34	0.001
	(4.42)	(0.005)
RtYear-2	-0.22	0.004
	(3.98)	(0.005)
RtYear+0	-0.75	0.014**
	(4.21)	(0.005)
RtYear+1	-9.47*	0.010
	(4.18)	(0.006)
RtYear+2	-4.91	-0.000
	(4.06)	(0.007)
RtYear+3	-12.71*	-0.002
	(5.82)	(0.006)
RtYear+4	-8.44	0.009
	(6.25)	(0.005)
Age (yrs)	0.36***	0.006***
	(0.04)	(0.000)
Female	19.57***	-0.033***
	(1.62)	(0.002)
HHIncome (1000's)	-0.06***	-0.000***
	(0.01)	(0.000)
Log(PopEstimate)	-10.46	0.038
	(18.02)	(0.063)
HHSize	6.25***	
	(0.68)	
HHNumKids	2.16*	
	(0.84)	
Log(FBCounts)	2.74	
	(14.83)	
Unemployment (%)	-0.91	
	(0.58)	
Log(TotEmployed)		0.019
		(0.033)
Log(Total GDP(1000s))		0.055
		(0.028)
Log(AvgPersonalIncome(1000s))		-0.095***
		(0.023)
Fixed Effects	County, State*Year, Race, EmpState	Race, Marital Status, Education, MSA, State*Year
Num. obs.	23,061	1,837,061
Num of Geographies	85 (Counties)	73 (MSAs)
Adj. R^2 (full model)	0.12	0.06
Adj. R^2 (proj model)	0.10	

***p < 0.001; **p < 0.01; *p < 0.05; +p < 0.1, SEs in parentheses clustered by geography

Note*:* The reader should be cautious in directly comparing the relative temporal trends across the two different outcomes as they capture the behavior across different geographies. On limiting the ATUS sample to counties completely within the BRFSS MSAs, 25 counties remain. In this restricted sample, when the relative time model for cooking times is repeated, we find that the effect of Grubhub Delivery manifests for both outcomes within the year of treatment (RtYear+0).

Figure A2. Distributions (overlapping) of predicted propensities of treatment between treated (light gray) and untreated (dark gray) county-year observations.

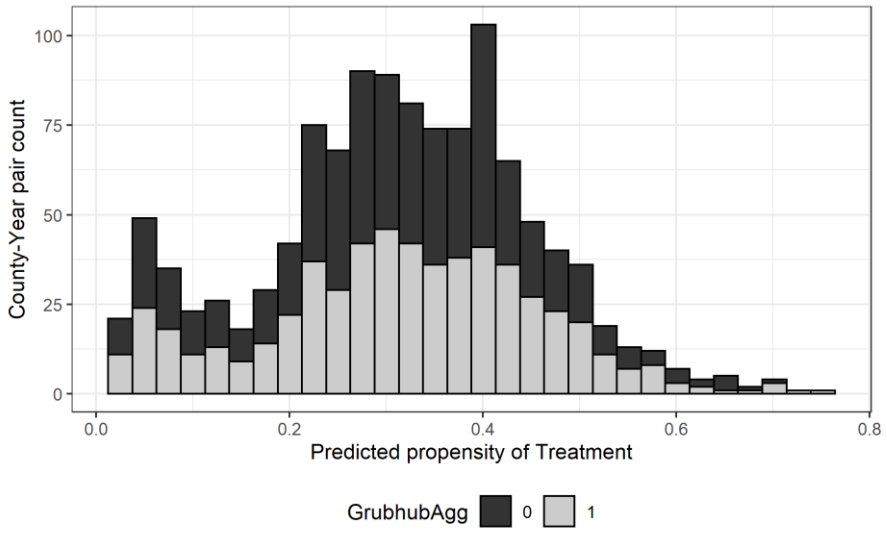

Table A8. Grubhub impact on Cooking Time PSM results 2005-19, eventually treated with GrubhubAgg only counties.

DV = CookingTime (mins)	PSM Matched Counties	PSM Matched Counties (only eventually treated)
GrubhubAgg	4.877	4.808
	(3.569)	(3.730)
GrubhubDelivery	-5.500*	-6.378*
	(2.478)	(2.729)
FamInc (1000's)	-0.053***	-0.058***
	(0.009)	(0.010)
HHSize	7.082***	7.272***
	(0.536)	(0.605)
Age (years)	0.357***	0.356***
	(0.048)	(0.052)
Female	21.680***	21.999***
	(1.502)	(1.680)
Log(FBCnts)	11.771	14.877
	(18.131)	(18.325)
Log(Population)	-65.043	-46.055
	(52.591)	(60.147)
Unemployment (%)	-0.215	-0.613
	(1.124)	(1.139)
Fixed Effects	Race, County, State*Year, Employment Status	
Num. obs.	16,184	13,888
Num. of Counties	176	85
Adj. R^2 (full model)	0.117	0.120
Adj. R^2 (proj model)	0.107	0.111

***p < 0.001; **p < 0.01; *p < 0.05, County Clustered SEs in parentheses

Table A9. Grubhub impact on Cooking Time placebo results 2005-19, eventually treated with GrubhubAgg only counties.

DV = cooking time	1 Baseline	2 Placebo Entry (-1 year)	3 Placebo Entry (-2 year)
GrubhubAgg	1.318	1.348	1.343
	(2.080)	(1.976)	(1.960)
GrubhubDel	-5.677**		
	(1.949)		
Placebo GrubhubDel		1.148	0.181
		(3.324)	(2.928)
Age	0.363***	0.362***	0.362***
	(0.044)	(0.046)	(0.046)
Female	19.590***	19.307***	19.306***
	(1.618)	(1.827)	(1.827)
FamIncome (1000s)	-0.061***	-0.059***	-0.059***
	(0.009)	(0.011)	(0.011)
HHSize	6.266***	6.623***	6.621***
	(0.681)	(0.744)	(0.745)
HHNumkids	2.157*	1.031	1.032
	(0.837)	(1.008)	(1.006)
Not In Workforce	16.310***	15.861***	15.861***
	(1.243)	(1.319)	(1.321)
Unemployed	19.098***	16.903***	16.904***
	(2.099)	(2.567)	(2.568)
Log(Population)	-5.152	-2.194	-1.621
	(18.850)	(22.165)	(22.404)
Log(FBCount)	1.069	13.463	13.338
	(15.036)	(20.232)	(20.291)
Unemployment(%)	-0.710	-1.486*	-1.480*
	(0.584)	(0.599)	(0.600)
Fixed Effects	Race, County*Year		
Num. obs.	23061	18565	18565
Num. Counties	85	85	85
Adj. R^2 (full model)	0.115	0.108	0.108
Adj. R^2 (proj model)	0.096	0.088	0.088

County clustered SEs in parenthesis $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Figure A3. Distribution of GrubhubDel Estimates on Cooking Time using leave one out.

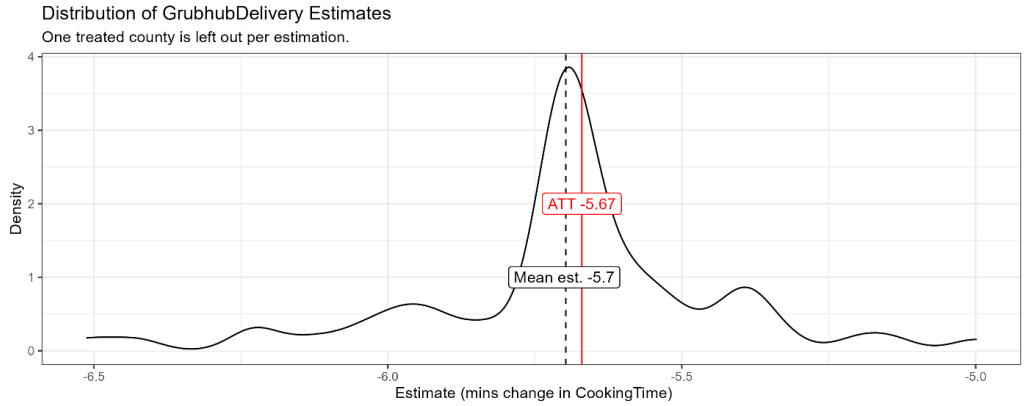

Figure A4. Estimated treatment effects per county among counties that eventually receive Grubhub.

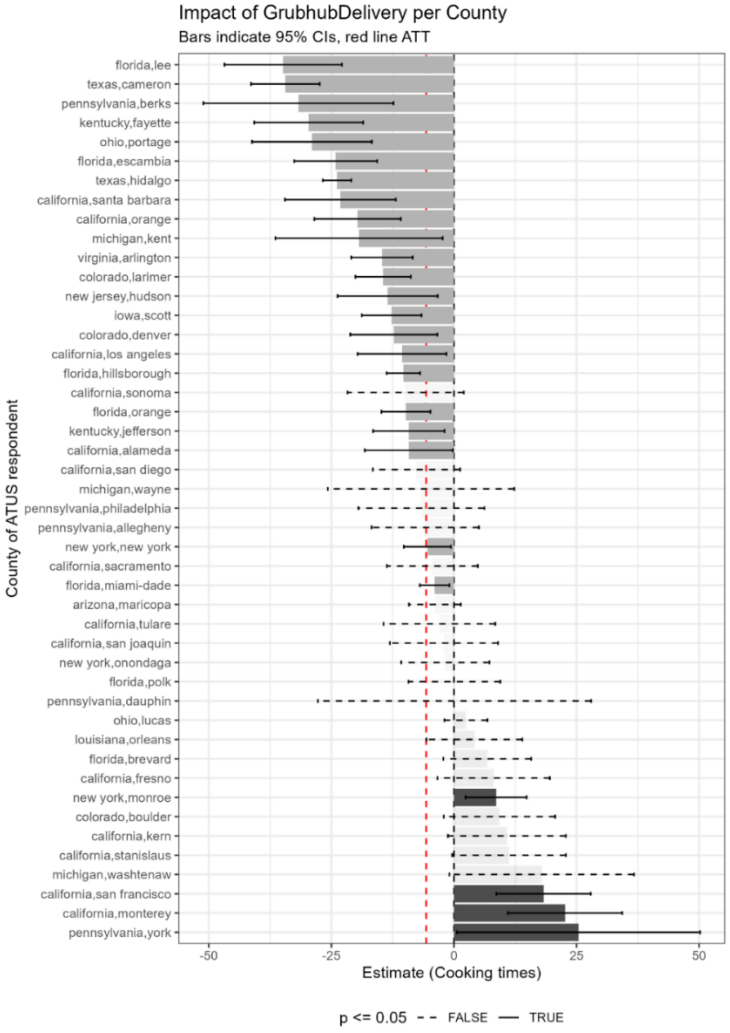

Table A10. Impact on Cooking Time controlling for interest in meal kits

DV = CookingTime (mins)	All Counties	Eventually Treated Counties
GrubhubAgg	-0.15	1.21
	(1.78)	(2.07)
GrubhubDelivery	-5.07**	-5.78**
	(1.89)	(1.92)
Age (years)	0.34***	0.36***
	(0.04)	(0.04)
Female	19.31***	19.58***
	(1.27)	(1.62)
FamInc (1000's)	-0.05***	-0.06***
	(0.01)	(0.01)
HHSize	5.76***	6.27***
	(0.56)	(0.68)
HHNumKids	2.32**	2.16*
	(0.70)	(0.83)
Log(Population)	-8.75	-9.96
	(18.39)	(18.48)
Log(FBCounts)	-9.90	4.90
	(11.93)	(15.03)
Unemployment (%)	-0.35	-0.74
	(0.45)	(0.58)
$MealKits_{Gtrends}$ [1]	1.63	2.63
	(1.52)	(1.81)
Fixed Effects	County, Race, State*Year, EmpState	
Num. obs.	31,259	23,061
Num. groups: COUNTY	181	85
Adj. R^2 (full model)	0.11	0.12
Adj. R^2 (proj model)	0.09	0.10

***p < 0.001; **p < 0.01; *p < 0.05; +p < 0.1, SEs clustered by counties in parentheses

[1] $MealKit_{GTrends}$ ($\mu = 0.13, SD = 0.35$) was measured as a binary indicator of non-zero interest expressed in search terms "Hello Fresh" or "Blue Apron" (the market leaders in US for meal kit providers) per geography. Since Google trends are captured in relative terms we used (Hall et al. 2018)'s approach of using a single geography (in our case San Francisco-Oakland CA) as the comparison point for all others to arrive at cross geography, cross keyword, over time comparable relative search volumes.

Table A11. Impact on Cooking Time of Grubhub and UberEats

	All Counties	Eventually Treated Counties
GrubhubAgg	0.03	1.15
	(1.77)	(2.12)
GrubhubDelivery	-4.29^{+}	-4.56
	(2.55)	(2.83)
Age (years)	0.34***	0.36***
	(0.04)	(0.04)
Female	19.32***	19.58***
	(1.27)	(1.61)
FamInc (1000's)	-0.05***	-0.06***
	(0.01)	(0.01)
HHSize	5.76***	6.25***
	(0.56)	(0.68)
HHNumKids	2.32**	2.17*
	(0.70)	(0.83)
Log(Population)	-8.77	-7.21
	(18.17)	(18.01)
Log(FBCounts)	-11.11	1.10
	(12.07)	(15.35)
Unemployment (%)	-0.35	-0.73
	(0.45)	(0.59)
UberEats	-1.28	-2.42
	(2.83)	(3.56)
Fixed Effects	County, Race, State*Year, EmpState	
Num. obs.	31,259	23,061
Num. of Counties	181	85
Adj. R^2 (full model)	0.11	0.12
Adj. R^2 (proj model)	0.09	0.10

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$, County clustered SEs (in parentheses)

Table A12. DiD2s 2nd Stage, Impact of Grubhub on Cooking Time

DV = CookingTime	(1) (2nd Stage) OLS Eventually Treated Counties
GrubhubAgg	0.12
	(0.17)
GrubhubDelivery	-7.11**
	(2.51)
N	21,577
First Stage Controls	FamInc (1000's), Age , Female, Race and Employment Status Dummies, County and Year FEs

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A13. Impact of Grubhub on Cooking Times controlling for changes in grocery delivery

DV = CookingTimes (mins)	BaseModel	Whole Foods	Instacart	Online Grocery
GrubhubAgg	1.32	2.80	3.13	3.11
	(2.08)	(2.71)	(2.56)	(2.60)
GrubhubDel	-5.68**	-6.41*	-6.50*	-6.98**
	(1.95)	(2.61)	(2.44)	(2.55)
Age (yrs)	0.36***	0.34***	0.34***	0.34***
	(0.04)	(0.05)	(0.05)	(0.05)
Female	19.59***	20.57***	20.56***	20.58***
	(1.62)	(1.90)	(1.90)	(1.90)
FamInc (1000's)	-0.06***	-0.06***	-0.06***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)
HHSize	6.27***	6.36***	6.35***	6.37***
	(0.68)	(0.82)	(0.82)	(0.82)
HHNumkids	2.16*	2.17*	2.19*	2.17*
	(0.84)	(0.94)	(0.93)	(0.94)
Not In Workforce	16.31***	16.58***	16.60***	16.58***
	(1.24)	(1.43)	(1.43)	(1.43)
Unemployed	19.10***	20.53***	20.55***	20.52***
	(2.10)	(2.43)	(2.44)	(2.44)
Log(Population)	-5.15	-33.11	-13.59	-25.31
	(18.85)	(29.07)	(28.13)	(32.16)
Log(FBCounts)	1.07	-13.35	-19.82	-15.89
	(15.04)	(15.59)	(16.83)	(15.55)
Unemployment (%)	-0.71	-0.91+	-0.57	-0.79
	(0.58)	(0.49)	(0.53)	(0.49)
Gtrends(`Whole Foods`)		-0.29		-0.34
		(0.23)		(0.21)
Gtrends(Instacart)			0.32	0.56
			(0.58)	(0.53)
Fixed Effects		County, Race, State*Year		
Num. obs.	23,061	17,317	17,317	17,317
Adj. R^2 (full model)	0.12	0.12	0.12	0.12
Adj. R^2 (proj model)	0.10	0.10	0.10	0.10

***p < 0.001; **p < 0.01; *p < 0.05; +p < 0.1, SEs clustered by County in parentheses

Table A14. Summary statistics of BRFSS SMART Panel from 2005-19 for 73 MSAs.

Variable	Mean	Std. Dev.	Min	Max
BMI	27.78	6.12	4.78	99.98
Log(BMI)	3.3	0.2	1.56	4.6
HHIncome(1000's)	52.04	26.5	7.5	82
Age (age group)	7.32	3.33	1	13
GrubhubAgg	0. 45		0	1
GrubhubDel	0.2		0	1
N	1,837,061			

Table A15. Grubhub entry dates by county

County FIPS	Grubhub Entry Year	Grubhub Delivery Entry
17031	2004	2015
55079	2004	2015
06075	2006	2015
36005	2006	
36047	2006	
36061	2006	2015
36081	2006	
36085	2006	
25009	2008	2016
25021	2008	
25025	2008	
06037	2009	2015
11001	2009	2015
42101	2009	2015
06001	2010	2015
06073	2010	2015
08013	2010	2015
08031	2010	2015
41051	2010	2015
53033	2010	2015
04013	2011	2015
06085	2011	2015
09003	2011	2016
09009	2011	
12086	2011	2015
13089	2011	2015
13121	2011	
24510	2011	2015
26161	2011	2016
42003	2011	2015
48113	2011	2015
48201	2011	2015
48209	2011	2015
48439	2011	
48453	2011	2015
48491	2011	2015
55025	2011	2016
02135	2012	
04019	2012	2015
06013	2012	
06059	2012	2015
06067	2012	2015
06071	2012	
06081	2012	
08001	2012	
08005	2012	
08035	2012	
08041	2012	2016
08059	2012	
08069	2012	2018
09001	2012	
09004	2012	2015
09007	2012	
09013	2012	
10003	2012	
12001	2012	2015
12011	2012	
12031	2012	2015
12057	2012	2015
12073	2012	
12095	2012	2015
12099	2012	
13067	2012	
13087	2012	
16055	2012	
17019	2012	2015
17043	2012	
17089	2012	
17097	2012	
17113	2012	
17197	2012	
18035	2012	
18097	2012	2015
18105	2012	2018
18157	2012	
19103	2012	
19169	2012	
20091	2012	
20161	2012	
24005	2012	
24021	2012	
24031	2012	
24033	2012	
25013	2012	2018
25017	2012	
26037	2012	2018
26045	2012	2018
26065	2012	2018
26073	2012	
26077	2012	2018
26081	2012	2016
26163	2012	2015
27053	2012	2015
27123	2012	
29019	2012	2018
29037	2012	
29047	2012	2016
29095	2012	2016
29165	2012	
29510	2012	2015
32003	2012	2015
34003	2012	
34007	2012	
34013	2012	
34017	2012	2015
34021	2012	
34023	2012	
34025	2012	
36001	2012	2015
36055	2012	2016
36059	2012	
36067	2012	2016
36083	2012	
36103	2012	
36109	2012	
36119	2012	
37037	2012	
37063	2012	2016
37081	2012	2018
37097	2012	2015
37135	2012	
37147	2012	
37183	2012	
39035	2012	2015
39041	2012	2015
39045	2012	
39049	2012	
39173	2012	
40017	2012	2018
40027	2012	2018
40109	2012	2018
41039	2012	2016
41067	2012	
42027	2012	
42029	2012	
42077	2012	
42091	2012	
42093	2012	
42095	2012	
44007	2012	2016
45051	2012	2018
45079	2012	2018
47037	2012	2015
47093	2012	2016
47149	2012	
48029	2012	2015
48041	2012	
48085	2012	
48121	2012	
48157	2012	
48339	2012	
48473	2012	
51003	2012	
51013	2012	2015
51059	2012	
51121	2012	
51510	2012	
51540	2012	
51600	2012	
51610	2012	
51760	2012	2016
51810	2012	2015
51830	2012	
53011	2012	
54061	2012	
91303	2012	
91311	2012	
06041	2013	
22033	2013	2018
30031	2013	
32031	2013	2018
35001	2013	2016
35043	2013	2016
36027	2013	
46099	2013	
48215	2013	2018
49035	2013	2016
12103	2014	
12115	2014	2018
13185	2014	
18141	2014	2018

2 APPENDIX B: SURVEY DESIGN

Table B1. Survey Questions

QNo.	Question	Question-Type
1	How old are you? - Under 18 (1) , 18-24 years old (2), 25-34 years old (3) , 35-44 years old (4) , 45-54 years old (5) , 55-64 years old (6) , 65+ years old (7)	Multiple Choice
2	How do you describe yourself? - Male (1) , Female (2) , Non-binary / third gender (3) , Prefer to self-describe (4) [Text], Prefer not to say (5)	Multiple Choice
3	What best describes your employment status over the last three months? - Working full-time (1) , Working part-time (2) , Unemployed and looking for work (3) , A homemaker or stay-at-home parent (4) , Student (5) , Retired (6) , Other (7)	Multiple Choice
4	What is your current marital status? - Married (1) , Living with a partner (2), Widowed (3), Divorced/Separated (4), Never been married (5)	Multiple Choice
5	How many people live or stay in this household at least half the time?	Text
6	How many children under 18 live with you?	Text
7	In which state do you currently reside?	Dropdown
8	Choose one or more races that you consider yourself to be: - White or Caucasian (1) , Black or African American (2) , American Indian/Native American or Alaska Native (3) , Asian (4) , Native Hawaiian or Other Pacific Islander (5) , Other (6) , Prefer not to say (7)	Multiple Choice
9	What is the highest level of education you have completed? - Some high school or less (1), High school diploma or GED (2), Some college, but no degree (3) , Associates or technical degree (4) , Bachelor's degree (5) , Graduate or professional degree (MA, MS, MBA, PhD, JD, MD, DDS etc.) (6) , Prefer not to say (7)	Multiple Choice
10	What was your total household income before taxes during the past 12 months? - Less than $25,000 (1) , $25,000-$49,999 (2) , $50,000-$74,999 (3) , $75,000-$99,999 (4) , $100,000-$149,999 (5) , $150,000 or more (6) , Prefer not to say (7)	Multiple Choice
11	What is your height?	Text
12	What is your weight in pounds (lbs)?	Text
13	Would you say that in general your health is ____ - Excellent (1) , Good (2) , Average (3) , Poor (4) , Terrible (5)	Multiple Choice
14	Now thinking about your physical health, which includes physical illness and injury, for how many days during the past 30 days was your physical health not good?	Text
15	Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?	Text
16	During the past 30 days, for about how many days did poor physical or mental health keep you from doing your usual activities, such as self-care, work, or recreation?	Text
17	Do you have any kind of health care coverage, including health insurance, prepaid plans such as HMOs, or government plans such as Medicare, or Indian Health Service?	Text
18	On average, how many hours of sleep do you get in a 24-hour period?	Slider
19	In a week on average how often do you perform rigorous exercise/physical activity (with at least 10 minutes of sweating or elevated heart rate)?	Slider
20	In a typical week, how often do you eat each of the following meals? Breakfast, Lunch, Dinner, Snacks – 0 to 7	Matrix
21	How often in a week do you eat the following? • Rows - Home-cooked Meals (1), Takeaway Meals (2), In-restaurant Meals (3), Cafeteria Meals (4), Grocery/Deli bought Meals (5), Frozen Meals (6), Fresh Fruits (not juice) (7), 100% Fruit Juice (8), Vegetables, Leafy greens, or Salads (9) • Columns - Never (0%) (1), Sometimes (25% or less) (2), About half the time (25-50%) (3), Most of the time (50-75%) (4), Always (5)	Matrix

22	How much (in dollars) do you approximately spend (per person) on the following per month? Groceries & Eating Out – 0 to 1000$	Slider
23	Are you the primary meal preparer in your household? - No (1) , Yes (2)	
24	In a week how often do you/someone in your household cooks the following meals? Breakfast, Lunch, Dinner, Snacks – 0 to 7	Matrix
25	In the last 24 hours how many times did you prepare a meal? - 0 (1) , 1 (2) , 2 (3) , 3 (4) , More than 3 (5)	Multiple Choice
26	How many minutes (on average) do you/your primary meal preparer spend cooking a single meal on average – 0 to 180 [On a weekday, On a weekend]	Slider
27	Indicate on a scale of 1-5, while cooking, how much your household relies on each of the following. • Rows – Fresh ingredients/ cooking from scratch - like fresh vegetables, meats, dairy and poultry (1) , Packaged/boxed/canned ingredients - like premixes, seasoning packets, portioned meal kits (2) , Frozen products - like frozen vegetables, meats, pre-made meal components (3) , Recipes from a book, online sources, apps etc. (4) • Columns - Never (1), Sometimes (2), About half the time (3), Most of the time (4), Always (5)	Matrix
28	Have you ever used any online food delivery services (like Grubhub or UberEats)? - No (1) , Yes (2)	Multiple Choice
29	When did you first order food online ever? - More than 5 years ago (1) , More than 2 years ago (2) , Last year (3) , This year (4)	Multiple Choice
30	Choose which of the following is true for the **majority** of your online food delivery orders. - I mostly order for myself/others (1) , Someone else mostly orders for me (2)	Multiple Choice
31	Select all the online prepared food delivery services that you have ever used. - Grubhub (1) , Postmates (2) , DoorDash (3) , UberEats (4) , Eatstreet (5) , Seamless (6) , ChowNow (7) , Others, please specify (8)	Multiple Choice
32	How often do you order food online? - At least once every 3 days (1) , At least once a week (2) , At least once every two weeks (3) , At least once a month (4) , Less than once a month (5)	Multiple Choice
33	How much do you generally spend per delivery order? - Less than 15$ (1) , Between 15-30$ (2) , Between 30-50$ (3) , More than 50$ (4)	Multiple Choice
34	Which of the following do you use online food delivery apps for (you can choose more than one)? - Ordering Delivery (1) , Ordering Pickup (2)	Multiple Choice
35	Which meals do you generally order using online food delivery (you can choose more than one)? - Breakfast (1) , Lunch (2) , Dinner (3) , Snacks (4) , Beverages (5)	Multiple Choice
36	On a scale of 1-5, how often do you order from the following type of restaurants using online delivery? • Rows - Fast-food restaurants (McDonalds, Taco Bell etc.) (1), Casual sit-down restaurants (2), Fine dining restaurants (3), Coffeeshops & Bakeries (4) • Columns - Never (1), Sometimes (2), About half the time (3), Most of the time (4), Always (5)	Matrix
37	For each of these please indicate on a scale of 1-5, how they influence your decision to order food online. • Rows – Delivery Time (1), Delivery and service fees (2), Variety in restaurant options (3), Convenience (4), How much time I have (5), How healthy the food is (6) • Columns - Never (1), Sometimes (2), About half the time (3), Most of the time (4), Always (5)	Matrix
38	Recall your behavior before you had tried online prepared food delivery services and indicate on a scale of 1-5 your agreement with the following statements. • Rows - I eat out more often because of online food delivery options. (1), Per order, I order	Matrix

	greater quantities online than I would in person at a restaurant. (2), I order unhealthier foods online than I would in person at a restaurant. (3), I often have leftovers from my online delivery orders. (4), I am more comfortable trying different restaurants online than I am in person. (5), I cook less often than before because I order food online (6), I dine-in at restaurants less because I order food online (7) • Columns - Strongly disagree (1), Somewhat disagree (2), Neither agree nor disagree (3), Somewhat agree (4), Strongly agree (5)	

Table B2. Descriptive Statistics of Key Variables from Survey

	Food & Eating Descriptives					
	Statistic	N	Mean	St. Dev.	Min	Max
Meal eating frequency per week	Breakfast	596	4.10	2.67	0	7
	Lunch	596	5.40	2.12	0	7
	Dinner	596	6.56	1.19	0	7
	Snacks	596	4.95	2.08	0	7
How often do you eat the following in a week	Home-cooked Meals	596	3.73	0.87	1	5
	Takeaway Meals	596	2.05	0.68	1	5
	In-restaurant Meals	596	1.67	0.59	1	4
	Cafeteria Meals	596	1.12	0.42	1	5
	Grocery/Deli bought Meals	596	1.77	0.78	1	5
	Frozen Meals	596	1.92	0.80	1	5
	Fresh Fruits (not juice)	596	2.73	1.21	1	5
	100% Fruit Juice	596	1.85	1.00	1	5
	Vegetables, Leafy greens, or Salads	596	3.08	1.11	1	5
Monthly spending per person	Groceries	583	291.08	173.57	0	1,000
	Eating Out	540	136.11	113.36	0	700
	PrimaryCook [0/1]	596	0.72	0.45	0	1
	HoursSpentCooking (out of last 24)	595	1.86	1.07	0	4
Weekly cooking frequency	Breakfast	595	3.37	2.63	0	7
	Lunch	595	3.99	2.36	0	7
	Dinner	595	5.53	1.62	0	7
	Snacks	595	3.03	2.59	0	7
	MinutesSpentCooking (Weekday)	596	36.30	21.61	0	180
	MinutesSpentCooking (Weekend)	596	42.70	27.83	0	180
How often do you use the following (1-5)	Fresh ingredients/ cooking from scratch - like fresh vegetables, meats, dairy and poultry	596	3.50	1.01	1	5
	Packaged/boxed/canned ingredients - like premixes, seasoning packets, portioned meal kits	596	2.60	0.94	1	5
	Frozen products - like frozen vegetables, meats, pre-made meal components	596	2.66	0.94	1	5
	Recipes from a book, online sources, apps etc.	596	2.44	0.99	1	5

Table B3. Correlation between Daily Cooking Time and Use of Online Food Delivery

DV = Avg. Daily Cooking Duration (mins)	Model 1	Model 2
Female	1.43	1.19
	(2.51)	(2.55)
Age (years)	0.16	-0.07
	(0.18)	(0.20)
Married	4.25**	4.93***
	(0.77)	(0.74)
HouseholdSize	5.03***	4.58**
	(0.75)	(1.07)
Children	-1.62	-1.46
	(1.12)	(0.96)
IncomeLvl	-0.71	-0.59
	(0.94)	(0.95)
IsPrimaryCook	2.11	2.91
	(1.47)	(1.60)
EverOrderedOnline	1.42	
	(1.13)	
FoodDelivery (This Yr)		14.14*
		(4.16)
FoodDelivery (Last Yr)		7.71+
		(3.78)
FoodDelivery (More than 2yrs ago)		-0.99
		(2.56)
FoodDelivery (More than 5yrs ago)		-1.48*
		(0.46)
Fixed Effects	Race, Education Lvl, Employment Status	
Num. obs.	594	594
Adj. R^2 (full model)	0.09	0.12
Adj. R^2 (proj model)	0.08	0.11

***p < 0.001; **p < 0.01; *p < 0.05; +p < 0.1, SEs in parentheses.

3 APPENDIX C: GOOGLE TRENDS DATA

The complexity of collecting Google Trends data (specifically region and time specific data on Grubhub and DoorDash) bears some discussion as well, despite the prevalence of such data in prior information systems and economics scholarship (Choi and Varian 2012, Hall et al. 2018, Park and Kim 2018). The challenge is that Google Trends only offers a bounded metric (1-100) of the relative intensity of search when those Trends are retrieved. This raises the question of how to compare across such searches of Trends (i.e. to compare across time and geography). To do so, we follow the approach described by Hall et al. (2018). Under this approach, we gather data for the search terms mentioned in the manuscript: e.g. "Grubhub" or "DoorDash" etc. by searching for them by metro area (See Trends help for how metro areas are defined). As Google Trends only allows for relative comparisons of trends between time and geographies and does not offer an absolute count of search results, each search contains both a control keyword ("food delivery") and control geography (San Francisco-Oakland, CA). These data therefore reflect the relative monthly levels of interest in the focal word (e.g. Grubhub) and the focal geography relative to the interest in "food delivery" in the San Francisco area over time. To estimate the average interest in a keyword per geography each year we average the monthly levels by that geography and year.