Journal of Economic Psychology 89 (2022) 102475

Contents lists available at ScienceDirect

Journal of Economic Psychology

journal homepage: www.elsevier.com/locate/joep

Tipping in crises: Evidence from Chicago taxi passengers during COVID-19☆

Sarah Conlisk

Federal Reserve Board of Governors, United States of America

ARTICLE INFO

JEL classification:
D91
D12
I15
M52
Z13

PsycINFO Classification:
2229
3020
3900
3920

Keywords:
Consumer behavior
Tipping
COVID-19

ABSTRACT

In early 2020, the novel coronavirus (COVID-19) spread to the United States and upended normal life. Using trip-level data on over 17 million taxi rides taken in Chicago from 2018–2021, I document how tipping behavior changed during the COVID-19 pandemic. I find that the average non-zero tip as a percent of the taxi fare increased 2 percentage points, or roughly 10%. Meanwhile, the likelihood that a passenger left a tip at all declined by roughly 5 percentage points, down from a pre-pandemic likelihood of 95%. My preferred specification suggests that the effect on the intensive margin dominates that in the extensive margin, leading to an aggregate increase in tipping generosity during the pandemic. I leverage granularity in the data to explore the mechanisms behind these trends and offer two explanations consistent with the data. First, passengers responded to the major economic shocks of the pandemic – unemployment and savings overhangs – by varying their tipping rates accordingly. Second, passengers internalized the increased risk of COVID-19 infection as an additional cost for taxi drivers and increased their tips as compensation. My analysis testifies to the sustainability of tipping in times of crises and offers theoretical insight into what drives tipping behavior.

1. Introduction

1.1. Importance of tipping

Tipping is a pervasive and significant feature of the American service economy. Although social norms vary across industries and locations, tips are frequently given to workers providing services, notably servers, bartenders, hairdressers, parking valets, taxi drivers, and tour guides (Star, 1988). And while individual tips tend to be modest, the total can be substantial, with some workers earning over half of their income in tips (Payscale, 2012). In the US restaurant industry alone, it was recently estimated that over $46 billion is earned each year through tips (Azar, 2011). Further, historical trends suggest that tipping is becoming more economically meaningful: while the tipping norm was 10% in late 19th century America, it rose to 15% in the middle of the 20th, and by the end of the 20th century had reached 20% in large cities (Post, 1997).

And yet, the voluntary nature of tipping does not comport with standard economic theory; why would a customer pay more for a service after it has been rendered? This question has inspired a robust interdisciplinary literature that seeks to understand tipping behavior (see Lynn (2006, 2015a, 2017) and Azar (2007, 2020) for reviews). Previous research has covered a variety of topics,

☆ I thank Michael Lynn for advice and mentorship throughout this project. All errors and omissions are my own responsibility. This research was not supported by any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The views expressed in this paper are solely my own and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of anyone else associated with the Federal Reserve System. Instructions and material for replicating my analysis are publicly available on Mendeley Data (Conlisk, 2021).

E-mail address: ssconlisk@gmail.com.

https://doi.org/10.1016/j.joep.2021.102475
Received 22 June 2021; Received in revised form 17 December 2021; Accepted 23 December 2021
Available online 19 January 2022
0167-4870/

including differences on the extensive and the intensive margins of tipping (Alexander et al., 2021; Haggag & Paci, 2014; Lynn, 2015b; Schwer & Daneshvary, 2000); income effects in tipping (Azar et al., 2015; Frank & Lynn, 2020; Tan & Zhang, 2020); the role of reciprocity in tipping (Lee & Sohn, 2020; Lynn, 2009, 2015a; Lynn & Grassman, 1990); and most recently, how the COVID-19 pandemic has impacted tipping behavior (Brewster & Gourlay, 2021; Lynn, 2021; Majid et al., 2021).

Working with a rich dataset of taxi trips taken in Chicago from January 2018 to March 2021, this study contributes to each of these research areas. First, I demonstrate how the COVID-19 pandemic has impacted tipping behavior in both the extensive and intensive margins. Second, I construct a proxy for passenger's household income and test for heterogeneity in the effect of the pandemic on tipping. Third, I examine whether COVID-19 tipping trends were additionally related to perceived and actual infection risk at the time of the taxi ride. My findings have practical implications for the viability of tipping in times of crisis and provide theoretical insight into the mechanisms underlying tipping.

2. Background and literature review

2.1. COVID-19 pandemic

As most research on tipping has taken place during periods of relative stability, the ongoing COVID-19 pandemic offers a new context for researchers to gain insight into tipping. COVID-19 is a highly infectious disease, transmitted through droplets from an infected person's cough, sneeze, or breath (Galbadage et al., 2020). On March 11th, 2020 the World Health Organization declared the disease outbreak a pandemic, and on March 13th, the president of the United States announced a national emergency. In order to slow the spread of the disease, the country went into lockdown; by late March, many states had closed schools, restaurants, bars, and other businesses. Citizens were banned from public gatherings and encouraged to stay home. When in public spaces, they were asked to wear masks and socially distance from others. The pandemic was not only a public health crisis, but an economic crisis as well, as the US economy shrunk 3.5% in 2020 (Crutsinger, 2021) and 20.5 million Americans lost jobs in April 2020 alone (Bureau of Labor Statistics, 2020). Notably, the economic toll of the pandemic was not felt equally. Job losses were concentrated among low-wage workers, and by April 2021 employment among the bottom third of earners was still down 30% from pre-pandemic levels (Chetty et al., 2020). Meanwhile, government-issued stimulus checks, rising stock markets, and reduced consumption led to a $18 trillion increase in wealth among U.S. households; of this excess savings, 70% went to the top 20% of earners (Batty et al., 2021). The outcome of these two shocks are often characterized as having a K-shaped effect on the economy: wealthy individuals gained wealth, while less wealthy individuals lost income when they lost their jobs, resembling the diverging strokes of the letter K when plotted (Saraiva, 2020).

From a practical standpoint, it is important to understand whether tips remain a dependable source of income for service workers during crises, especially as we prepare for climate change disasters and future pandemics. From a theoretical perspective, whether tipping behavior changed under the significant lifestyle, economic, and public health shocks of the COVID-19 pandemic provides insight into the mechanisms that drive tipping.

2.2. Tipping in COVID-19 pandemic

Recent research by Lynn (2021) provides some initial insight into how the pandemic has affected tipping. Analyzing data provided by a pizza delivery drivers in Texas from January 2020 to July 2020, Lynn finds that the average tip increased after COVID-19 was declared a national emergency and remained elevated through July 2020. In a secondary study of data from Square payment systems, Lynn finds broadly similar results; average tip as a percent of the bill increased by roughly five percentage points for distanced transactions at restaurants and increased by two percentage points at face-to-face quick service restaurants. These trends align with a recent survey from two small businesses that found customers report they would tip more (in both the extensive and intensive margins) after the pandemic than before (Majid et al., 2021). However, Lynn also identified a decrease in average tip percentages at full service restaurants with face-to-face interactions after the start of the pandemic. Lynn speculates that the overall increase in tip amounts is due to a heightened perception of server needs during the pandemic, and suggests that any decreases in tipping rates can be attributed to the changing nature of face-to-face service in the pandemic. Relatedly, Brewster and Gourlay (2021) conduct a hypothetical experiment and find that masks are not likely to have a meaningful impact on the tips that restaurant customers leave, although servers with masks were generally perceived as less friendly.

Lynn's evidence that tipping broadly increased during the pandemic is compelling and prompts further questions. For example, are the positive effects on tipping in the pandemic that Lynn observed driven by more customers deciding to tip or by customers leaving a larger tip when they do? For another, how well do these effects generalize across customers or time? This paper builds upon the findings of Lynn (2021) to probe the mechanisms underlying pandemic tipping in 3 respects: (1) I estimate the impact of COVID-19 separately for both the extensive and intensive margin; (2) I examine whether these effects are heterogeneous across (i.e. moderated by) income; and (3) I consider whether tips are additionally related to true or perceived COVID-19 infection risk at time of trip.

2.3. Predictors of tipping on the extensive and intensive margins

The motivations behind tipping have fascinated researchers across the fields of economics, psychology, sociology, and marketing for decades (see Lynn, 2006; Azar, 2007; Lynn, 2015a; and Azar, 2020 for reviews). Notably, the tipping decision has two components: (1) the consumer decides whether to tip; and (2) the consumer decides how much to tip. These two decisions are clearly linked and unsurprisingly share several motivations. In a web-based study of consumers, Lynn (2015b) demonstrates that reward motives (e.g. "to reward good service") and altruistic motives (e.g. "to help servers") are associated with both greater tip sizes and increased likelihood of leaving a tip, as reported by the consumer. Additional evidence for the impact of service quality on both tip frequency and size points to the similarities in the underlying decision processes. For instance, consumers in South Africa who perceived "quality service" (i.e. neat, friendly, attentive and prompt) from their car guards tipped more frequently and at higher rates (Saunders & Lynn, 2010). Likewise, trips from the rideshare platform Uber that receive higher quality ratings from passengers are more likely to be tipped and tipped more generously (Chandar et al., 2019). Notably, the relationship between service quality and tips extends beyond the subjective. Chandar et al. (2019) found both tip likelihood and non-zero tip size decreased when drivers sped, braked hard, and accelerated quickly. Another shared predictor of tipping on the extensive and intensive margins is degree of server–consumer interaction: taxi rides where the passenger and driver converse are 1.33x more likely to be tipped (Aydin & Acun, 2019), and evidence from the restaurant industry suggests that servers can increase the size of their tips by touching and complimenting diners, as well as addressing them by name (Ebesu Hubbard et al., 2003; Seiter, 2007; Seiter & Weger, 2013).

However, the tipping literature has also identified a number of effects that differ on the extensive and intensive margins. For instance, studying tips at a beauty salon, Schwer and Daneshvary (2000) found that the cost of a haircut, identifying as female, and whether one cares about their appearance were all positively associated with tip size but unrelated to the likelihood of tipping. Particularly compelling are instances in which the effects on the extensive and intensive margins go in opposite directions. In one such instance, Lynn (2015b) found that duty motives (e.g. "I tip to obey social norms") increased the likelihood of tipping but decreased the size of those tips left across a variety of services. In another instance, Lynn (forthcoming) manipulated the fullness of a tip jar and observed that a full tip jar increased the likelihood of tipping but decreased the size of the average tip left. These two studies suggest that pressure to leave a tip – whether internally or externally motivated – increases likelihood of leaving a tip but at the expense of the tip amount.

Interestingly, pressure to leave a larger tip increases tip sizes while decreasing the likelihood of tipping. For example, Haggag and Paci (2014) take advantage of a change in default tip selection for taxi rides and demonstrate that higher defaults increase non-zero tip sizes and drivers' tip incomes on aggregate, but also increase the likelihood a passenger will "stiff", or not tip, by 50%. The authors reason that passengers perceived higher default tips as unfair and chose to penalize drivers by not tipping. Similar evidence can be found in Alexander et al. (2021) who show that increasing tip recommendations for a laundry service led to greater tips but reduced likelihood of tipping. However, Alexander et al. also find that higher tip recommendations did not affect customer satisfaction, patronage, or spending. This runs contrary to the penalty justification for stiffing and provides little clarity on the mechanisms underlying tipping on the extensive margin.

Reviewing this evidence, consumers respond to pressure to leave a tip vs. not by tipping more frequently, but leaving smaller tip amounts when they do so. Conversely, consumers respond to pressure to leave a larger tip by leaving greater tip amounts, but by tipping less frequently. Thus, observing that COVID-19 was associated with contradicting effects on the extensive and intensive margins may suggest that the pandemic affected tipping through pressure mechanisms. This literature highlights the relevance of examining tipping in the pandemic along both the extensive and intensive margins.

2.4. Effects of wealth and costs on tipping

Under standard consumer theory, demand for a good is an increasing function of income (Engel, 1857). Considering tips to be a normal good, one can anticipate that such an income effect exists in tipping: when consumers are wealthier, they tip more. Existing tipping literature lends some support to this theory. For example, Lynn (2009, 2015b) finds a positive correlation between consumer income and their reported likelihood of tipping in occupations that are routinely tipped. Similarly, in an analysis of 13 million taxi trips taken in NYC, Elliott et al. (2017) demonstrate that passengers originating in locations with lower average income per capita are consistently more likely to stiff.

The positive relationship between consumer's income and tip behavior is observed in the intensive margin as well (Lynn, 2009) and remains significant even after controlling for a number of potentially confounding demographics such as dining frequency (Parrett, 2006). Specifically in a context similar to taxi rides, Chandar et al. (2019) identify a positive relationship between tips an Uber driver receives and the median income of a passenger's zip code. However, the evidence on this point is not unanimous, as Elliot et al. fail to find a corresponding relationship with median income of a passenger's pickup area among New York City taxis.

Given that income is correlated with a large number of customer demographics that may also impact tipping behavior (i.e. education, ethnicity (Lynn, 2009)), stronger causal inferences can be derived by examining how tips respond to shocks in a customer's income. In one such study, Tan and Zhang (2020) estimate that a one standard deviation increase (decrease) in stock returns is associated with a .3% greater (smaller) daily average tips. This association is limited to trading hours and robust to other large news events, which Tan and Zhang interpret as evidence that the relationship operates through an income effect (tips increase with income), rather than a sentiment effect (tips increase with happiness). Possible evidence of an income effect is also presented in Azar et al. (2015), who conduct a field experiment in which restaurant customers are randomized to receive extra change before tipping. They observed that customers who receive a greater amount of extra change ($12 vs. $3) tipped their server larger amounts, indicating that positive income shocks inspire greater tips.[1] In a related literature, researchers have found that positive shocks to income also increase charitable giving (Auten et al., 2002).

[1] Importantly, the authors caveat that the data may not fully support evidence of an income effect, given that the observed relationship between tip amount and extra change is independent of whether the customer actually returned the change. However, a pro-social trait such as altruism may be positively associated with tip amount and likelihood of returning the change, which could explain why the income effect was observed in both cases.

And yet, other evidence suggests that tips are somewhat insensitive to changes in a customer's budget. For instance, tips tend to increase linearly with bill size, contrary to the quadratic trend expected if customers were concerned with cost (Lynn & Sturman, 2003). A recent field experiment from Frank and Lynn (2020) provides further evidence against a wealth effect; server's tips increased when a magician performed at their customer's tables, but were independent of the size of the magician's tip.

Given that the literature concerning the effect of income shocks on tipping is mixed there is need for more research on the subject. The COVID-19 pandemic was a source of two non-trivial economic shocks: job losses and significant savings overhangs. If there is an income effect in tipping, one would expect to see tipping generosity decline among customers who lost jobs in the pandemic but increase among those who grew their savings. Thus, studying how tipping behavior in the pandemic interacts with these economic shocks may offer evidence in support of an income effect in tipping.

2.5. Equity theory in tipping

Lynn and Grassman (1990) pose that from a rational choice perspective, customers tip in order to buy equitable relationships. Their hypothesis is rooted in equity theory (Adams, 1965; Walster et al., 1973) which offers that individuals are socialized to feel anxiety or distress when participating in an unequal exchange. Adams (1965) represents equity theory with the formula

$$\frac{O_A}{I_A} = \frac{O_B}{I_B} \tag{1}$$

where O_A and O_B refer to person A's and person B's outcomes from the exchange while I_a and I_B refer to A's and B's inputs to the exchange, respectively. When the equality is not met, the exchange is considered to be unequal. Applying equity theory to the context of tipped professions, the costs of providing a service are the inputs for service worker A (I_A), and tips received are A's outcome (O_A). Meanwhile, customer B inputs tips (I_B), and receives service quality as an outcome (O_B) (Lynn & Grassman, 1990). Customers who perceive their exchange is unequal will tip more in order to restore equity in the exchange, a mechanism also referred to as the norm of reciprocity.

Existing tipping literature offers a fair amount of support for such equity motives in tipping. In the service context, equity theory predicts that tips increase in proportion to the consumer's perception of (1) the quality of service they receive and (2) the cost for the worker of providing the service. Consistent with (1), customers report that the factor most driving their tip behavior is the desire to "to reward good service" (Lynn, 2009). And researchers have found that customers do leave tip amounts that are positively and reliably related to their evaluations of service, although this service-tipping relationship is somewhat weaker than consumers claim (Lynn & McCall, 2000).

In support of (2), there is some evidence that customers internalize worker's cost of providing a service and tip accordingly. For example, Lee and Sohn (2020) identify a positive relationship between inclement weather and taxi tipping in NYC: passengers are more likely to tip above 20% in extreme temperatures and when it is precipitating. They hypothesize that passengers recognize the driver's increased efforts in poor weather, and attempt to restore equity by tipping more.[2] In addition, Lynn et al. (2012) find that customers tip more the longer they stay at a restaurant, an effect that is largest for customers with the smallest bill sizes, and interpret this relationship as recognition of an opportunity cost: consumers are aware that their lingering costs the server additional customers and so voluntarily compensate servers for that lost opportunity. Finally, recent field experiments have also found that restaurant customers left higher tips when they witnessed servers being mistreated by other customers (Hershcovis & Bhatnagar, 2017), as well as when servers were yelled at or criticized by their supervisors (Jin et al., 2020). These results are consistent with equity theory because consumers are likely to perceive the negative treatment of the server as a cost of providing service.

As proposed by Majid et al. (2021), the increased risk of a COVID-19 infection can be considered an additional cost from the service worker. To the extent that customers recognize this additional input, they will reciprocate with greater tips, restoring equity in the exchange. Through this mechanism, equity theory manifests as a discretionary form of hazard pay. Hazard pay is a common assumption in the economics literature: workers in more dangerous jobs will demand a higher wage rate (Viscusi, 1978), and the market will offer higher wages for riskier work (Thaler & Rosen, 1976). While the formal wage in the taxi market may be slow to adjust for the additional risk of COVID-19, equity theory predicts that passengers who internalize this additional cost will take it upon themselves to compensate the driver by tipping more. Thus, investigating how tipping on the intensive margin varies with perception of COVID-19 infection risk may lend empirical support to motives of reciprocity in tipping.

3. Data and methods

3.1. Raw data

As part of their open data initiative, the City of Chicago provides publicly available data on taxi rides through the Chicago Data portal (Levy, 2021a). This dataset is a nearly comprehensive record of each trip taken since 2013, and includes 23 variables containing trip-level information. This study subsets the data to all trips taken between January 2018 and April 2021 and makes use of the following variables

[2] This study adds an interesting dimension to the literature on weather and tipping. Notably, Cunningham (1979) identified a positive relationship between sunshine and tipping, presumably operating through the positive effects of pleasant weather on mood. However, Flynn and Greenberg (2012) fail to replicate with a significantly larger sample. It seems possible that the positive effects on tipping of both sunshine and inclement weather offset each other, leading to the null results in Flynn and Greenberg (2012).

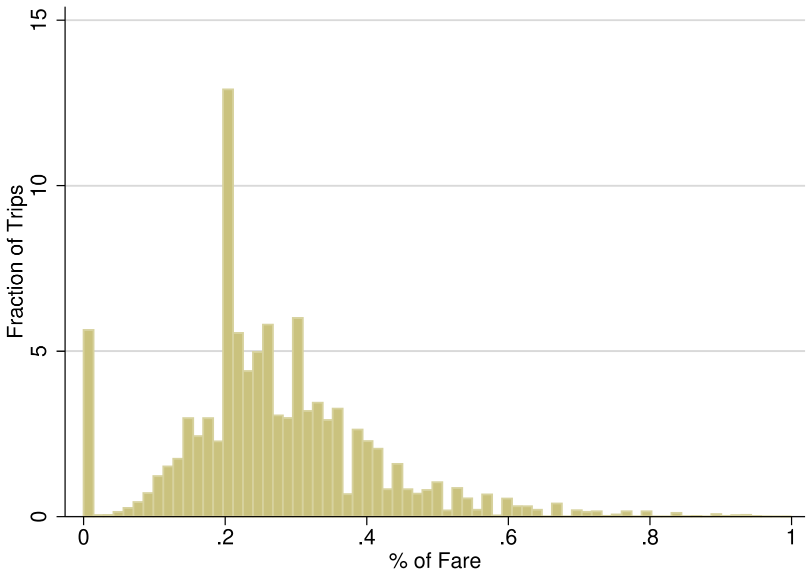


Fig. 1. Tip as a % of the taxi fare.

- Trip End Timestamp (15-min interval)
- Trip Duration (in seconds)
- Pickup Location (one of 77 community areas[3])
- Fare Amount (in $)
- Tip Amount (in $)
- Payment Type (Cash or Credit Card)
- Taxi ID (6,181 different taxis in sample)

I complement the trip-level data with three other sources. First, I incorporate data on the median income for each community area provided by the Chicago Metropolitan Agency for Planning (CMAP, 2015). Second, I merge in daily counts of COVID-19 hospitalizations since March 1st, 2020 available through the Chicago data portal (Levy, 2021b). Third, I consider the 2020 presidential election results for Chicago (Chicago Board of Election Commissioners, 2020). The election results are provided at the ward level, which is not a direct mapping to community areas. I address this by identifying the three wards that had the highest Repubican vote share for the 2020 presidential election, and consider the community areas that comprise those wards as relatively “red" regions.[4] Further description of these data and the cleaning process can be found in Appendix B. The material needed for replicating my analysis is available on Mendeley Data (Conlisk, 2021).

3.2. Sample

Given that records on cash tips are unreliable and often missing, I first filter the data to include only those trips paid with a credit card. Next, I follow the procedure outlined in Tan and Zhang (2020) and include only trips with fare amounts that are greater than $3.25 (the base rate for a ride [5]) but less than $1,000, as well as trips with a positive duration in seconds. On this subset of trips I create three variables: *Tip?*, an indicator for whether the passenger left a tip; *Tip %*, or the tip amount as a percentage of the fare, conditional on the tip being positive; and *Pandemic*, an indicator for whether the trip occurred after March 13th, 2020, the national emergency was declared.[6] I further drop from the sample any trips where *Tip %* is greater than 100%, so that exceptionally large tips would not bias the main estimates.[7] The distribution of the tip as a percent of the fare is shown in Fig. 1. Evidently, 20% is still the most common value of *Tip %* in the sample, which aligns with previous research on taxi tip rates in NYC (Elliott et al.,

[3] Map of community areas provided in Appendix A.

[4] Chicago is a very blue city; the Republican candidate received under 16% of the vote share overall and there is no ward in which they received the majority of votes. However, in wards 41, 38, and 19, the Republican candidate received 47%, 40%, and 38% of votes, respectively, and thus I consider passengers coming from community areas in those wards as “red", or more likely to identify with the Republican Party, relatively to the the average Chicago passenger.

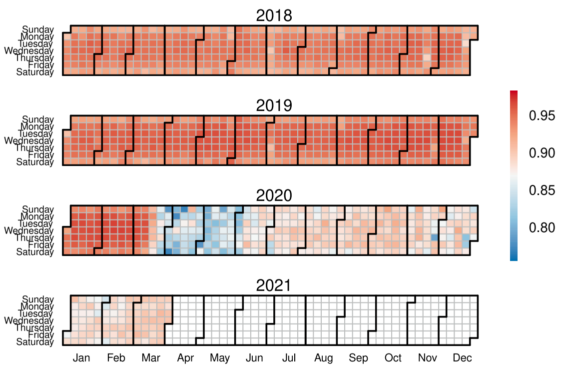
[5] See Taxi Rate Calculator.

[6] Granted, this decision is somewhat arbitrary, as COVID-19 spread to communities with different severities at different times. As a robustness check, I repeat my main analysis using a definition of the pandemic that began on March 20th, the day that Chicago’s governor issues a stay-at-home order.

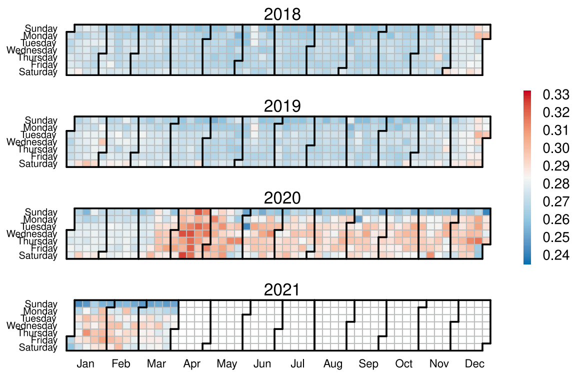
[7] Doing so reduced my sample by .4%, or by 73,144 trips. As a robustness check, I repeat my analysis on the full sample, and winsorize *Tip %* at the 99th percentile instead of dropping large values. There is no significant change in estimates, which are available upon request.

Table 1
Descriptive statistics for Chicago taxi rides (Jan 2018–April 2021).

	Mean	sd	p25	p50	p75
# of Rides (Daily Average)	25,142	7,592	20,732	26,384	30,365
Tip? (Daily Average)	95	1.5	94	95	96
Tip % (if positive)	27	12	20	24	32
Fare	16	15	6.5	9	20
Trip Duration (min)	16	19	7	11	21
Median Income of Pickup Area	91,493	19,783	83,575	99,732	107,246
COVID-19 Hospitalizations (Daily)	34	38	7	23	42
"Red" Passengers	.135	.34	0	0	0
Observations	17,757,921				



(a) *Tip?*



(b) *Tip %*

Fig. 2. Daily Average tipping trends.

2017). The distribution is skewed to the right, with most passengers tipping more than 20%, while roughly 5% of passengers did not tip at all.

Table 1 reports the summary statistics for the final sample of over 17 million taxi trips taken from January 2018–April 2021. On average, there is a record for 25,132 trips each day, of which 95% of passengers leave a tip. The average tip in the sample is 27% of the fare, whereas the median is 24%, reflecting the right skewed distribution shown in Fig. 1.[8] The average fare for a ride in the sample is $16 and the average ride lasts roughly 16 min. The median household income of the area in which the passenger is picked up is $91,493, while the average number of COVID-19 related hospitalizations is 34, and roughly 14% of trips are taken by passengers I classify as coming from red locations.

In Fig. 2, I present calendar heat maps for the two outcomes of interest: *Tip?* and *Tip %*. Each square corresponds to the average of that variable for a given day; for instance, the very first square in Panel A indicates that roughly 93% of passengers left a tip on Jan 1, 2018. Clearly, both statistics are fairly stable up until the spring of 2020, when the country entered lockdown in response to COVID-19. In the second half of March 2020 the percent of riders who left a tip plummeted about 15 percentage points and remained well below the pre-pandemic mean even a year later. Meanwhile, Panel B suggests that the average non-zero tip as a percent of the fare increased by several percentage points during the pandemic, and has been elevated since then, at tipping rates similar to Christmas day, a time in which tipping rates are unusually high (Greenberg, 2014).

Although these trends in daily averages are compelling, they may be driven by several outliers or reflect the changing characteristics of taxi rides during the pandemic. For instance, evidence from the UBER ride-sharing platform that tips are greater for airport trips (Chandar et al., 2019) may generate a downward bias on average estimates, given that tourism and business trips shrank dramatically during the pandemic. The regression analysis I employ takes advantage of trip-specific characteristics to help control for this confounding variability.

3.3. Methods

I formally test for the effect of the pandemic on tipping behavior with the equation

$$Y_{r,i,t} = \alpha + \delta X_r + \gamma_i + \beta COVID_t + \epsilon_{r,i,t} \quad (2)$$

[8] This might seem high for an average tip percent. One possibility is that passengers are calculating their tip off of the total fare, which includes additional costs such as tolls or taxes.

Table 2
Effects of COVID-19 pandemic on taxi tipping.

	Tip?			*Tip %*			*Tipping generosity*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
COVID	−5.74***	−5.71***	−3.89***	1.62***	1.92***	1.81***	−0.12	0.25*	0.67***
	(0.18)	(0.18)	(0.15)	(0.14)	(0.09)	(0.09)	(0.15)	(0.10)	(0.10)
Constant	94.78***	94.84***	94.69***	27.19***	31.84***	32.87***	25.77***	30.13***	30.97***
	(0.04)	(0.04)	(0.04)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
Observations	17757921	17757921	17757921	16812577	16812577	16812577	17757921	17757921	17757921
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Loc. F.E.s	No	No	Yes	No	No	Yes	No	No	Yes

*$p < .05$, **$p < .01$, ***$p < .001$.
Cells report estimates and associated S.E.s in parentheses.
Controls include fare amount and trip duration.
Fixed effects include pickup location.
In all estimates standard errors are clustered by Taxi ID.
Tip? indicates whether a passenger left a tip.
Tip% is the tip as a percent of the fare, conditional on the tip being positive.
Tipping generosity is the tip as a percent of the fare, including zero tips.

where $Y_{r,i,t}$ is the dependent variable for trip r in pickup area i at time t, representing either the outcome *Tip?*, the likelihood that the passenger left a tip, or *Tip %*, the tip as a percent of the taxi fare, conditional on the tip being positive. I additionally provide estimates for *Tipping generosity*, which includes both zero and non-zero tips as a percent of the total fare, and captures the aggregate effect of the pandemic on tipping behavior. The main coefficient of interest is β, which is an estimate of how $Y_{r,i,t}$ has changed since COVID-19 was declared a national emergency in the US. X_r denotes a vector of controls for each trip r, namely the duration of the trip in minutes and the fare of the tip, while γ_i represents fixed effects for the pickup location i, one of Chicago's 77 community areas. I follow Haggag and Paci (2014) and cluster standard errors for all estimates at the driver level.

4. Results

4.1. Main effects of the pandemic

In Table 2, I present estimates for the effect of the pandemic as described in Eq. (2) across the extensive margin (columns 1–3), intensive margin (columns 4–6) and on aggregate (columns 7–9). The coefficient on COVID in column 1 indicates that the proportion of passengers that left a tip dropped 5.74 percentage points since the pandemic began in March 2020, down from a pre-pandemic mean of 94.8%. Meanwhile, the coefficient in column 4 demonstrates that the average tip left as a percent of the fare increased by about 1.62 percentage points since COVID-19, up from a pre-pandemic average tip rate of 27.2%. One concern with these simple differences in means is that characteristics of the typical ride or passenger changed during the pandemic, and this shifting sample could be responsible for observed trends. Columns 2 and 5 testify that the effects of the pandemic on both *Tip?* and *Tip %* are robust to the inclusion of controls for the fare amount and the duration of the trip in minutes. In columns 3 and 6 I add fixed effects for the pickup location of the rider in an attempt to control for any shifts in ridership that might have occurred during the pandemic. While the estimate on *Tip?* is somewhat attenuated, it is still strong and negative, with a 3.9 percentage point reduction in the likelihood that a passenger will leave a tip. Meanwhile, the estimated effect of COVID-19 on *Tip %* remain positive and significant, at almost 2 percentage points. The relative consistency of the estimates across columns 1–3 and 4–6 suggest that shifting characteristics of trips are unlikely to be biasing the estimates observed, and that the majority of variation in *Tip?* and *Tip %* can be attributed to effects of the pandemic.

Taken together, these results indicate seemingly contradictory effects of the pandemic on tipping behavior; while fewer passengers left tips, those who did left a significantly higher amount. One potential explanation is that the passengers who stopped tipping altogether during the pandemic were also the ones who tipped on the low end of the distribution of *Tip %* to begin with. Simply removing some of the population of low tippers from the pool would inflate *Tip %*. In columns 7–9 in Table 2 I provide estimates for *Tipping generosity*, a measure of *Tip %* that also includes passengers who do not tip, which helps address the issue of a changing population of tippers. Column 7 signals that on the aggregate, the increased number of "stiffers" in the pandemic offset the elevated tipping rates, leading to an insignificant change in tipping generosity overall. However, columns 8 and 9 indicate that controlling for trip-level characteristics and fixed effects for pickup location boosts the effect of the pandemic on *Tipping generosity* to be positive and significant, although attenuated to an increase of .3-.7 percentage points. Consequently, one can infer that the shifting population of tippers may explain some, but certainly not all of the increase in tipping rates. My preferred specification in column 9 also reinforces the findings of Lynn (2021) that the pandemic increased tipping generosity in contexts where the service did not substantially change,[9] although to a lesser extent than the 2–5 percentage point increase in tips that Lynn observed.

[9] The main change in taxi rides during the pandemic was the requirement of a mask (Exec. Order No. 43, 2020), which occurred on June 26, 2020

Notably, the conflicting trends along the extensive and intensive margins during the pandemic coincide with the evidence on tipping defaults; higher defaults are associated with greater non-zero tips as a percent of the bill, as well as average tips received by drivers overall, but are accompanied by an up to 50% increase in stiffing rates (Alexander et al., 2021; Haggag & Paci, 2014). Alexander et al. reason that such effects are plausible because (i) default options convey information about the expected contribution, which guides the behavior of those willing and able to conform with the implied norm, but (ii) may discourage those unable to meet these norms into not tipping. Interpreting the pandemic as a de facto increase in social norms of tipping, whereby putting pressure on consumers to tip more, is consistent with equity theory; passengers that perceive COVID-19 risk as an additional cost for the worker will perceive that the tipping norm has proportionally increased. I explore evidence for this equity mechanism in Section 4.3.2.

4.2. Robustness in main results

One concern with the standard OLS approach of (2) is that standard errors may be correlated beyond the Taxi ID (e.g. by pickup location or by time of day), resulting in deceivingly small standard errors (Bertrand et al., 2004). I attempt to control for this with a secondary model, that uses two stages to estimate the effect of the pandemic on tipping as shown in Eq. (3) and Eq. (4) below.

$$Y_{r,i,t} = \alpha + \delta X_r + \gamma_i + Z_t + \epsilon_{r,i,t} \tag{3}$$

$$Z_t = \beta Covid_t + v_t \tag{4}$$

In Eq. (3) I modify Eq. (2) to include a full set of indicators for each date t in the sample, such that $t \in$ {Jan 1, 2018, Jan 2, 2018 ... March 31, 2021}. The resulting vector of coefficients Z_t represent fixed effects for each day, which I regress on an indicator for the pandemic in Eq. (4). β becomes the coefficient of interest, and the issue of multiple levels of clustered errors is eliminated. As presented in Appendix Table D1, the size and significance of estimates from the two-stage regression are very comparable, bolstering confidence in the original estimates from Table 2.

Appendix Table D2 provides several other robustness checks of the main results. Columns 1, 4, and 7 correspond to the preferred specifications presented in columns 3, 6, and 9, respectively, of Table 2 but use a definition of pandemic that begins on March 20th, the day that Chicago's governor issued a stay-at-home order. These estimates are virtually the same as those that rely on the March 13th definition of the pandemic in Table 2. In columns 2, 5, and 8 I reproduce the estimates on a subset of the data that excludes trips to and from community areas that contain airports.[10] This helps to control for the substantial decrease in tourism during the pandemic, which may bias estimates given evidence from Uber that tips are systematically higher for airport trips (Chandar et al., 2019). Notably, these estimates replicate the main results but are slightly more positive than those in Table 2. This indicates that the pandemic decreased tipping likelihood less among local passengers than traveling ones and increased tip sizes more among local passengers than traveling ones. Such heterogeneity comports with a recent survey emphasizing how local consumer support for small businesses increased during the pandemic via tipping (Majid et al., 2021). Lastly, in columns 3, 6, and 9 of Table D2 I add in fixed effects for the taxi ID (presumably controlling for the driver), the month, and the day of the week (i.e. Sunday, Monday, etc.) that the trip was taken. These additional controls are justified by research identifying significant driver and seasonal effects, as well as more generous tips on Wednesdays and Fridays (Chandar et al., 2019; Flynn & Greenberg, 2012; Greenberg, 2014). This full set of fixed effects does not meaningfully change the magnitude or significance of the estimates, further building confidence in the main results.

In Appendix Table D3 I provide a third robustness check, that regresses one of four daily average tip outcomes – (1) *Tip ?*; (2) *Tip %*; (3) *Tip %* (median); and (4) *Tipping generosity* – on the outcome of that day exactly 1 year prior and an indicator for the pandemic. This specification will explicitly control for any general time trends and again eliminate seasonal effects that may be biasing the coefficients (Greenberg, 2014). The key takeaways remain: the likelihood that a passenger tips is significantly lower during the pandemic, while both the average and median non-zero tip increased. Without any trip-level or location controls, the net effect on *Tipping generosity* is negative, reflecting what was observed in column 5 of Table D1.

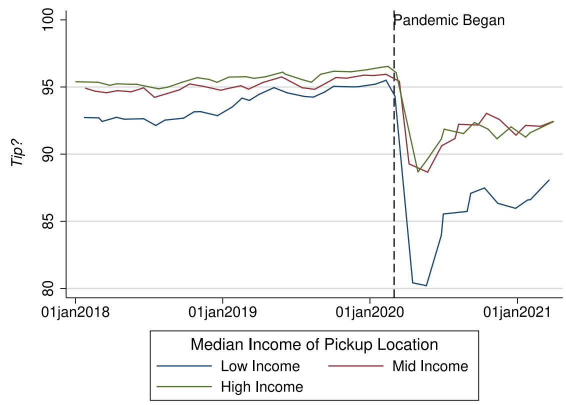
4.3. Interactions

The results from Sections 4.1 and 4.2 indicate that the pandemic was associated with significant changes in tipping behavior: customers were less likely to tip, but tipped greater amounts when they did. Next, I examine heterogeneity in (i.e. moderation of) these associations to shed light on possible mechanisms through which the pandemic may affect tipping.

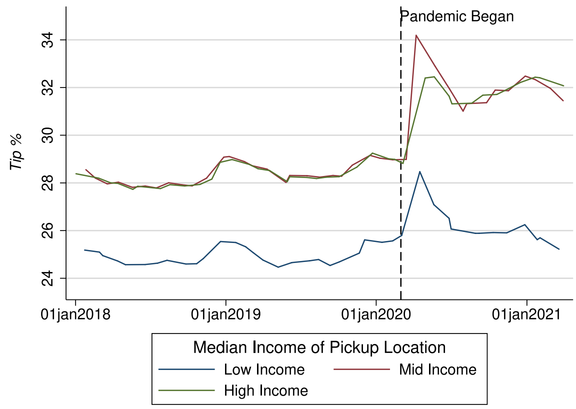
4.3.1. Heterogeneity/moderation by income

First, I explore whether tipping trends might be driven by the economic shocks of the pandemic, consistent with an income effect in tipping. Job losses may force passengers to eliminate discretionary expenses like tipping, while savings overhangs may embolden passengers to increase their tips. I draw from evidence that job losses during the pandemic were more common in lower-income households while wealth gains were concentrated among higher-income households (Batty et al., 2021; Chetty et al., 2020), and proceed to investigate whether COVID-19's effect on tipping behavior differs by a passenger's income, which I proxy with the median

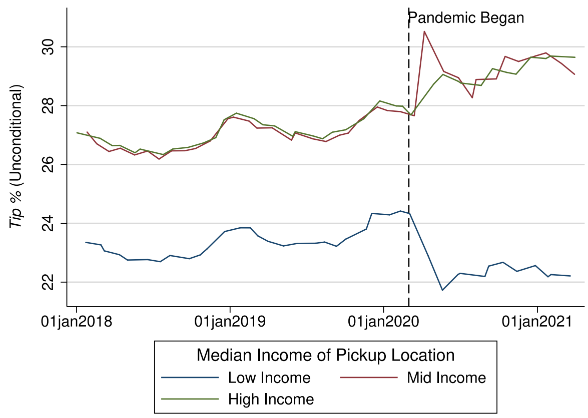
[10] Chicago has 2 airports: O'Hare airport is in the O'Hare community area, Midway airport is in the Garfield Ridge community area



(a) *Tip?*



(b) *Tip %*



(c) *Tipping generosity*

Fig. 3. Effect of COVID-19 on tipping by passenger income proxy.

income of a passenger's pickup area. Specifically, I classify rides into one of three terciles relative to the rest of the data – low-, middle-, or high-income – depending on pickup location, and use these terciles to analyze the pandemic effect by passenger's income. If these interactions indicate that passengers from higher-income areas increased their tips more than passengers from lower-income areas during the pandemic, or that the increase in stiffing rates was driven by lower-income passengers, this may be evidence of an income effect in tipping.

I provide visual evidence for these interaction effects in Fig. 3, where I plot monthly averages for each outcome of interest by income tercile. Panel A demonstrates that passengers from the lowest-income tercile were less likely to leave a tip prior to the pandemic, which is consistent with recent research on stiffing rates among NYC taxi passengers (Elliott et al., 2017). The declaration of a national emergency in March 2020 led to a drop in *Tip?* for all terciles, but the drop was substantially larger for passengers from low-income areas. Monthly averages since 2021 demonstrate that the level of *Tip?* had not recovered and the gap for passengers from low-income areas remains exacerbated. Panel B tells a parallel story: passengers from lower-income areas have consistently tipped lower percentages than passengers from middle- and high-income terciles and the increase that *Tip %* has experienced during the pandemic is primarily driven by passengers from middle- and high-income areas. In panel C, I plot monthly averages of *Tipping generosity* to visualize heterogeneity in the aggregate effect of the pandemic. Here, the diverging rates of tipping generosity between middle- and high-income locations and low-income locations is evocative of a K shape; the pandemic led to more generous tipping behavior among passengers from high- and middle-income locations, while passengers from lower-income areas became more stingy with their tips.

Although these plots are compelling evidence for an income effect in tipping, systematic differences in trip-level characteristics during the pandemic may be biasing the average estimates. I formally test for heterogeneous effects of the pandemic with Eq. (5), in which I estimate the effect of the pandemic, β, separately for each tercile.

$$Tip_{r,i,t} = \alpha + \delta X_r + \gamma_{income} + \beta COVID_t + \beta_{income} COVID_t + \epsilon_{r,i,t} \tag{5}$$

Table 3
Interaction effects between pandemic and income.

	Tip?		*Tip %*		*Tipping generosity*	
	(1)	(2)	(3)	(4)	(5)	(6)
	b/se	b/se	b/se	b/se	b/se	b/se
Mid Income	1.41***	0.08	3.41***	−0.01	3.59***	0.01
	(0.05)	(0.18)	(0.03)	(0.09)	(0.03)	(0.10)
High Income	1.96***	−0.12	3.38***	−0.04	3.72***	−0.06
	(0.05)	(0.19)	(0.03)	(0.09)	(0.03)	(0.10)
COVID	−7.30***	−4.60***	1.06***	0.79***	−0.90***	−0.36***
	(0.23)	(0.21)	(0.13)	(0.09)	(0.12)	(0.10)
COVID ×Mid Income	4.27***	1.61***	2.32***	1.87***	3.15***	2.02***
	(0.24)	(0.24)	(0.17)	(0.14)	(0.16)	(0.14)
COVID ×High Income	3.55***	1.24***	2.42***	2.29***	3.04***	2.29***
	(0.29)	(0.27)	(0.21)	(0.18)	(0.22)	(0.20)
Constant	93.65***	94.71***	24.90***	32.89***	23.32***	30.99***
	(0.06)	(0.13)	(0.03)	(0.07)	(0.03)	(0.07)
Observations	17757921	17757921	16812577	16812577	17757921	17757921
Controls	No	Yes	No	Yes	No	Yes
Pickup location fixed effects	No	No	No	No	No	No

$+p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.
Cells report estimates and associated S.E.s in parentheses.
Controls include fare amount and trip length in seconds.
In all estimates standard errors are clustered by Taxi ID.
Tip? indicates whether a passenger left a tip.
Tip% is the average non-zero tip as a percent of the fare.
Tipping generosity is the average tip as a percent of the fare, and includes zero tips.
The coefficient on COVID is the effect of the pandemic for passengers traveling from low-income locations.
The coefficient on COVID x Mid Income is the effect for middle-income relative to low-income passengers.
The coefficient on COVID x High Income is the effect for high-income relative to low-income passengers.

In this specification, $income \in [1, 3]$ such that $(income = 1)$ represents the community areas in the lowest tercile of median household income, $(income = 2)$ represents community areas in the middle-income tercile, and so on. This allows the estimate of β_{income}, or the effect of COVID-19 pandemic on tipping behavior, to vary by income tercile of pickup location. Meanwhile, γ_{income} controls for average tip behavior for each of the three income terciles prior to the pandemic, conditional on trip-level characteristics. Because there are only three terciles, the model will absorb the coefficient on the lowest-income tercile by default. Thus, the β coefficient on $COVID$ will represent the effect for passengers from the low-income tercile, while $\beta + \beta_2$ represents the effect of the pandemic for passengers from the middle-income tercile, and $\beta + \beta_3$ for high-income terciles. When presented in a table, this model is intuitive for discerning how the effects of the pandemic differ for passengers coming from middle and high, relative to low, income locations.

Estimates for Eq. (5) are presented in Table 3. The coefficients in column 1 confirm the main takeaway from panel A of Fig. 3. Passengers from low-income areas were 7.3 percentage points less likely to tip during the pandemic, while this decrease was substantially smaller for passengers from middle and high-income areas, who decreased tipping likelihood only about 3–4 percentage points. Column 2 demonstrates that the twice-as-large effect magnitude for passengers from low-income areas remains robust to the inclusion of controls for fare amount and trip duration, although is attenuated by several percentage points. Likewise, columns 3 and 4 showcase that the positive effect of the pandemic on *Tip %* is primarily driven by passengers from middle and high-income areas, who tipped about 3 percentage points more when they tipped. And columns 5 and 6 combine the effects along the extensive and intensive margins to estimate aggregate trends in *Tipping generosity*: average tips from passengers in low-income areas fell during the pandemic, dominated by greater stiffing rates, but remained elevated for passengers coming from middle- and high-income locations.

The heterogeneity observed in *Tip?* is consistent with an income effect in the event that passengers from lower-income areas were more exposed to negative economic shocks of the pandemic such as job losses, and chose to conserve money by tipping less. Given the evidence that wealth gains during the pandemic were concentrated among wealthier households (Batty et al., 2021), the data also support an income effect in *Tip %*. Passengers traveling from middle- and high-income locations left tips that were roughly 3 percentage points higher than pre-pandemic rates, while passengers from lower-income locations left tips only 1 percentage point higher. On aggregate, the estimates of tipping generosity during the pandemic were K-shaped, in sync with the aggregate economic trends. However, I want to underscore that a passenger's pick-up location is a rather crude proxy for income and that this analysis should be considered with that limitation in mind. Future research that precisely identifies the direction of a shock to a passenger's income will be needed to make any definitive claims about wealth effects in tipping.

4.3.2. Role/impact of infection risk

Second, I consider whether tipping trends on the intensive margin are further associated with infection risk. This analysis is motivated by an application of equity theory (Adams, 1965), that supposes passengers increase their tips in order to offset the greater risk of a COVID-19 infection for the driver during the pandemic; in practice, equity theory operates as a discretionary form of hazard pay. I push on this mechanism by investigating whether Chicago taxi passengers leave greater tips on trips where the perceived risk

Table 4
Heterogeneity by infection risk.

	Tip %			*Tipping generosity*		
	(1)	(2)	(3)	(4)	(5)	(6)
	b/se	b/se	b/se	b/se	b/se	b/se
COVID	1.96***			0.81***		
	(0.20)			(0.18)		
COVID ×Trip Duration (min)	−0.01			−0.01		
	(0.01)			(0.01)		
Trip Duration (min)	−0.04***			−0.03***		
	(0.01)			(0.00)		
COVID Hospitalizations (100)		0.64***	0.73***		0.16	0.24*
		(0.11)	(0.12)		(0.11)	(0.12)
Red ×COVID Hospitalizations (100)			−0.54**			−0.47*
			(0.18)			(0.21)
Constant	32.87***	35.85***	35.86***	30.97***	31.77***	31.78***
	(0.03)	(0.18)	(0.18)	(0.03)	(0.19)	(0.19)
Observations	16812577	282662	282662	17757921	317471	317471
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pickup location fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

*$p < .05$, **$p < .01$, ***$p < .001$.
Cells report estimates and associated S.E.s in parentheses.
Controls include fare amount and trip duration.
In all estimates standard errors are clustered by Taxi ID.
Daily hospitalizations are calculated on a 12-day moving average.
Tip? indicates whether a passenger left a tip.
Tip% is the average non-zero tip as a percent of the fare.
Tipping generosity is the average tip as a percent of the fare, and includes zero tips.
The coefficient on Red x COVID Hospitalizations is the effect of hospitalization rate on tipping for red passengers relative to other passengers.

of a COVID-19 infection is higher. Common knowledge on how diseases spread maintains that the likelihood a passenger infects a driver with COVID-19 increases with time spend in the taxi, as well as the prevalence of COVID-19 in the community at the time of the trip. Thus, I look at two sources of heterogeneity for infection risk during the pandemic: (1) trip duration in minutes and (2) the rolling 12-day average of the COVID-19 hospitalizations in Chicago, which is a proxy for prevalence of COVID-19, and thus risk of infection, on any given day.[11] I focus on the *Tip %* measure since passengers whose tip amount is motivated by equity theory will likely already be tipping. I also provide estimates for *Tipping generosity*, driven by the same logic as before: if greater risk of COVID-19 infection is correlated with low-tipping passengers ceasing tipping this could look like hazard pay, when the change is instead due to a shifting sample of tippers. Notably, I limit the analysis that considers COVID-19 hospitalization admissions to trips taken after March 13th, which will net out the previously established effects of the pandemic on tipping.

Table 4 tests how tipping rates vary with infection risk. Column 1 indicates that longer trips are associated with lower tipping rates across the whole sample, a trend unaffected by the pandemic. This relationship is inconsistent with a theory of hazard pay if passengers believe risk of COVID-19 infection increases with time spent in the same vehicle. Meanwhile, the positive and significant coefficient in Column 2 supports a mechanism of hazard pay: when COVID-19 is more prevalent in the community, passengers tip more to offset the greater cost for taxi drivers. Specially, column 2 suggests that every additional 100 COVID-19 hospitalizations in Chicago during the pandemic is associated with a .64 percentage point increase in the average tip among passengers who tip. When estimated for both tipping and non-tipping passengers this effect becomes insignificant, as shown in column 5.

In summary, there is some evidence that passengers increase tip sizes under heightened risk of COVID-19 infection in the community. However, the lack of significance on trip duration indicates they do not participate in this form of hazard pay when they themselves are the source of infection risk. It is possible that this is due to comparative optimism bias, where individuals perceive their risk of COVID-19 infection as lower than others (Kuper-Smith et al., 2020). Another explanation is that hospitalization admissions are correlated with some other factor that increases tipping generosity, and hazard pay motives are not driving the observed increase in tip sizes. For instance, number of rides per day is highly correlated with hospitalization rate, as I show in Appendix E. Perhaps, passengers recognize that taxi drivers are receiving less income on slow days and tip to help workers out of altruism, a commonly recognized motive for tipping (Lynn, 2015a).

While this is alternative explanation is plausible, I exploit further variation in perception of infection risk to bolster support for a mechanism of hazard pay. Given the high publicity of COVID-19 as a topic during the 2020 presidential campaign, I assume that the recognition of the risk of COVID-19 infection can vary across party lines and thus have a differential impact on the instinct to increase tips as hazard pay. Although Chicago remains a predominately blue city, I code passengers coming from community

[11] I construct a 12-day window to reflect that hospital admissions occur 10–12 days after infection, on average (Mayo Clinic, 2020). I use rolling averages rather than a 12-day lag to account for passengers who have imperfect information about the underlying prevalence of COVID-19 in their community, and thus update their perceptions of risk as news about cases, in addition to hospitalizations, comes in.

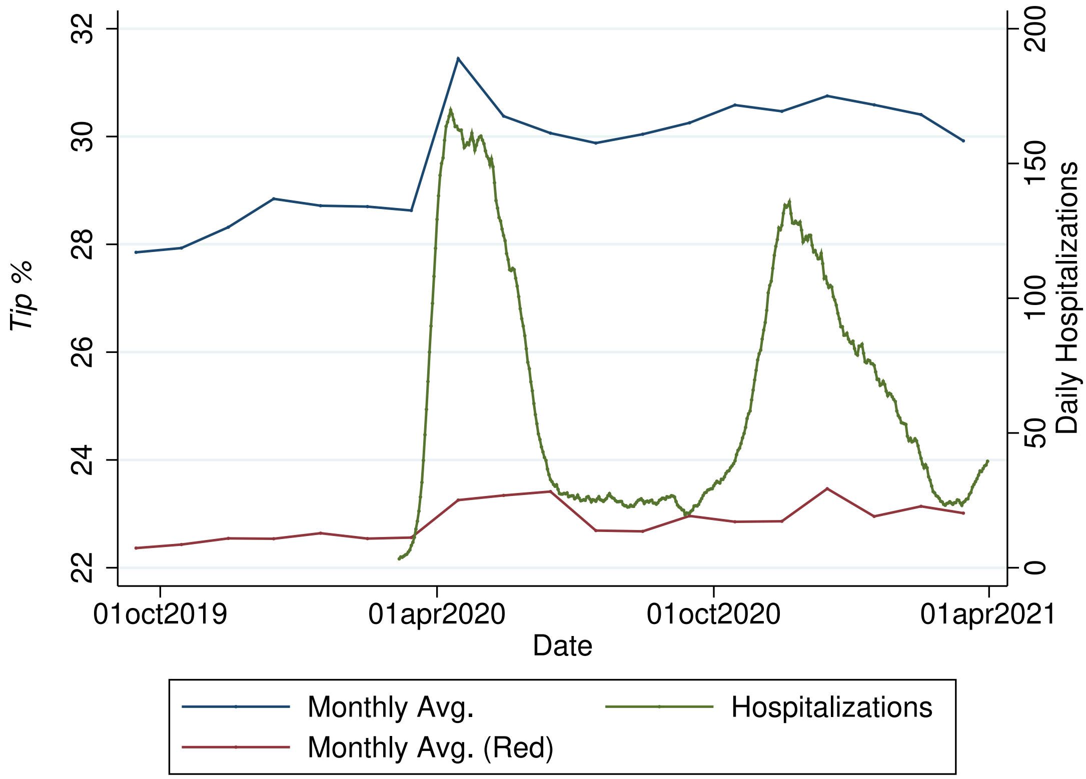


Fig. 4. Perceived infection risk and *Tip %*.

areas that are in wards with the highest Republican vote share in the 2020 presidential location as relatively "red" and interact that indicator with the rolling average of hospital admissions. A mechanism of hazard pay predicts that the coefficient on the interaction between red and hospitalizations is negative, indicating that the politicization of the pandemic has led passengers more likely to be Republican to be less likely to perceive a need to compensate the risk of infection with a higher tip. Formally, I estimate the following equation

$$Tip_{r,i,t} = \alpha + \delta X_r + \gamma_i + \beta Hospitalizations_t + \beta_R Hospitalizations_t + \epsilon_{r,i,t} \quad (6)$$

where the coefficient of interest is β_R, and $R \in \{0, 1\}$ to capture whether the relationship between tipping and hospitalization rate is weaker for passengers from relatively red community areas relative to all other passengers.

Estimates for Eq. (6) are presented in column 3 of Table 4. Tip sizes from passengers from relatively red locations are significantly less sensitive to increased hospitalization rates when tipping: the majority of passengers leave tips that are .73 percentage points higher for every additional 100 hospitalizations at time of trip, while this relationship is reduced to .19 percentage points for passengers from relatively red areas. Column 6 demonstrates that the significance of these results holds when estimated over the total population of tippers and non-tippers.

Fig. 4 provides an intuitive visualization of the results in column 3. Certainly, passengers from relatively red locations in Chicago tipped less prior to the pandemic. But they were less sensitive to the steep increase in hospitalizations in April 2020 and maintained tipping rates similar to pre-pandemic rates throughout 2020 and into 2021. Meanwhile, passengers from blue locations increased tipping rates by over 2 percentage points when hospitalizations first rocketed, and slightly elevated them again in response to the second wave of COVID-19 following the holiday season.

This analysis lends support to a mechanism of hazard pay during the pandemic. When hospitalization admissions increased, a majority of passengers responded by tipping higher percentages. However, this response was not universal; passengers from relatively red regions of Chicago were less likely to tip at greater rates when COVID-19 was more prevalent. Given the politicization of recognizing COVID-19 infection risk, this heterogeneity provides additional support for hazard pay motivated by equity theory; passengers who do not perceive that the exchange relationship has changed due to risk of infection will not increase tips.

5. Conclusion

Tipping is an economically meaningful and behaviorally curious feature of the American economy that has inspired a robust literature. However, most research on tipping has been completed in times of relative stability. The lifestyle, public health, and economic shocks of the 2020 coronavirus pandemic offer a new context for researchers to gain insight into tipping. Notably, Lynn (2021) has studied tipping during the pandemic and identified an increase in average tips in the majority of service contexts. The extent of and the mechanisms behind this increase are practically and theoretically interesting, and warrant further investigation.

Building upon Lynn (2021), this study leverages a high frequency publicly available dataset from January 2018–March 2021 to examine how tipping behavior among Chicago taxi passengers changed during the COVID-19 pandemic along the extensive and intensive margins. Further, it exploits granularity in the data to control for trip-level characteristics and explore possible mechanisms for this effect. I find that while passengers were 5 percentage points less likely to tip during the pandemic, those that did left tips roughly 2 percentage points higher, for a 7.5% average increase in the amount tipped. My preferred specification suggests that the effect on the intensive margin dominates that in the extensive margin, leading to an aggregate increase in tipping generosity during the pandemic. These findings are consistent with the main takeaway from Lynn (2021) that customers tipped more after the pandemic began. However, they also highlight that effects along the extensive and intensive margins are not always consistent, and underscore the importance of measuring both in future tipping research.

Interestingly, opposing effects in the extensive and intensive margins mirror research examining default tips: introducing tip defaults increases the average non-zero tip amount customers leave but leads to fewer customers leaving a tip at all. Observing a similar response during COVID-19 suggests an analogous mechanism: the pandemic increased how much customers thought they should tip. Such pressure is likely to have inspired greater tips from some customers but also prove to be insulting/prohibitive to others, who ceased tipping at all.

I bolster confidence in these main estimates with a series of robustness checks. Specifically, I provide comparable estimates under alternative empirical frameworks that (1) compare tipping behavior across unique days of the year to control for seasonal effects and (2) estimate the model in two stages, which sidesteps the issue of multiple levels of clustered errors. I also demonstrate that these effects remain in specifications that use an alternative definition of when COVID-19 began, consider additional trip-level controls, and exclude trips involving airports. Notably, I find that removing airport trips puts upward pressure on estimates, leading fewer passengers to stiff in the pandemic, and increasing the average non-zero tip size by roughly 3 percentage points instead of 2. These results indicate that the mechanisms leading passengers to increase tips during the pandemic are more salient among local passengers, which aligns with recent surveys documenting consumer support of local businesses through tipping (Majid et al., 2021).

Next, I explore heterogeneity in these trends to shed light on the mechanisms by which the pandemic may be affecting tipping. I show that the decline in tip likelihood during the pandemic is concentrated among passengers traveling from low-income locations; meanwhile, increases in average non-zero tips are driven by passengers from middle- and high-income locations. Combining these effects across the extensive and intensive margins leads to an aggregate increase in tips among passengers from middle- and high-income locations but a decrease among those coming from low-income locations. This evidence aligns with research on the disparate effects of COVID-19 economic shocks – job losses were concentrated among low-income individuals, while wealthier households experienced savings booms – and suggests that the trends in tipping during the pandemic may be driven by underlying changes in passenger wealth: passengers experiencing financial losses cut back on the discretionary act of tipping just as passengers experiencing gains increased tips. While such income effects are widely recognized in consumer theory and observed in related contexts such as charitable giving (Auten et al., 2002), the research on how tips respond to shocks in income remains somewhat mixed. Specifically, tips have been found to increase when customers receive extra change and to mimic movements in the stock market, but are unrelated to additional costs such as larger bill sizes or tips given to magicians (Azar et al., 2015; Frank & Lynn, 2020; Lynn & Sturman, 2003; Tan & Zhang, 2020). This study joins research on stock market fluctuations in providing evidence for an income effect in losses as well as gains, and is the first to document that negative income shocks may lead to reductions on the extensive margin of tipping. Further, the persistence of these trends over nearly a year during the pandemic is somewhat stronger evidence of an income effect, as such consistent effects cannot be due to the mood boosting (lowering) properties of gaining (losing) wealth that compromise short term studies of income effects (Azar et al., 2015; Tan & Zhang, 2020). However compelling, it is important to note that pickup location remains a rather crude proxy for a passenger's income shock. Further research that considers better identified economic shocks – such as stimulus checks or changes in base taxi fare – will reveal more on the relationship between a consumer's budget and tipping behavior.

Lastly, I consider whether tips during the pandemic are additionally related to greater risk of COVID-19 infection, of which I consider two sources: (1) the length of time a passenger spends with the driver in the taxi and (2) COVID-19 hospitalization rate at time of trip. While the relationship for trip duration is insignificant, I find that the daily COVID-19 hospitalization rate is positively associated with non-zero tip sizes during the pandemic. This result suggests that passengers may be participating in a discretionary form of hazard pay: when the community prevalence of COVID-19 is higher, so is infection risk, and passengers tip their drivers more as compensation for this greater cost of providing the taxi service. However, it is possible that the positive relationship between tips and hospitalizations is confounded by seasonal effects or altruistic tendencies during periods of low ridership. To address such concerns, I take advantage of the politicization of the pandemic and show that this effect ceases to exist among passengers traveling from relatively red regions of Chicago. This interaction bolsters support for a theory of hazard pay that is motivated by equity theory: customers who perceive the driver's cost of providing a taxi ride has gone up will increase their tip amount to maintain equity in the exchange, while customers who do not perceive an additional cost will not.

Although equity motives have been studied in the tipping literature, the focus has been on how consumers reciprocate in response to the quality of the service they receive (Lynn, 2001, 2003). This study contributes to a smaller body of research that observes increases in tips when service is more costly, such as in circumstances of dangerous driving conditions (Lee & Sohn, 2020), lost opportunity for additional customers (Lynn et al., 2012), and employee mistreatment (Hershcovis & Bhatnagar, 2017; Jin et al., 2020). Given the new appreciation for service workers sparked by the pandemic, a collective desire to compensate them more is not altogether surprising.[12] Furthermore, interpreting the pandemic as putting upwards pressure on tipping norms is consistent with the evidence of tip defaults on the extensive and intensive margins; customers tip higher amounts, but fewer customers tip. Research on whether tipping rates remain elevated throughout the roll-out of vaccines will provide additional insight into a mechanism of hazard pay and equity motives.

Ultimately, this study testifies to the sustainability of the tipping model in crises. Despite the significant economic and societal upheaval of the pandemic, the majority of passengers continued to tip, and many began to tip larger amounts, leading to an average increase in the tips that drivers receive. Not only does this highlight the enduring popularity of giving tips to service workers, but also underscores the benefits of tipping as a voluntary form of price discrimination: passengers can adjust their tips to the shocks of the pandemic and still afford the taxi service. The evident resilience and utility of tipping speaks to its longevity as a pricing model and stresses the relevance of future research on the topic.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.joep.2021.102475.

References

Adams, J. S. (1965). Inequity in social exchange. In *Advances in experimental social psychology (Vol. 2)* (pp. 267–299). Academic Press.

Alexander, D., Boone, C., & Lynn, M. (2021). The effects of tip recommendations on customer tipping, satisfaction, repatronage, and spending. *Management Science*, *67*(1), 146–165.

Auten, G. E., Sieg, H., & Clotfelter, C. T. (2002). Charitable giving, income, and taxes: An analysis of panel data. *American Economic Review*, *92*(1), 371–382.

Aydin, A. E., & Acun, Y. (2019). An investigation of tipping behavior as a major component in service economy: The case of taxi tipping. *Journal of Behavioral and Experimental Economics*, *78*, 114–120.

Azar, O. H. (2007). The social norm of tipping: A review 1. *Journal of Applied Social Psychology*, *37*(2), 380–402.

Azar, O. H. (2011). Business strategy and the social norm of tipping. *Journal of Economic Psychology*, *32*(3), 515–525.

Azar, O. H. (2020). The economics of tipping. *Journal of Economic Perspectives*, *34*(2), 215–236.

Azar, O. H., Yosef, S., & Bar-Eli, M. (2015). Restaurant tipping in a field experiment: How do customers tip when they receive too much change? *Journal of Economic Psychology*, *50*, 13–21.

Batty, M. M., Deeken, E., & Volz, A. H. (2021). *Wealth inequality and COVID-19: Evidence from the distributional financial accounts (No. 2021-08-30-2)*. Board of Governors of the Federal Reserve System (US).

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics*, *119*(1), 249–275.

Board of Election Commissioners (2020). 2020 General election results. https://chicagoelections.gov/en/election-results-specifics.asp.

Brewster, Z. W., & Gourlay, K. (2021). The Mask Effect on the tips that customers leave restaurant servers. *International Journal of Hospitality Management*, *99*, Article 103068.

Bureau of Labor Statistics (BLS) (2020). *Payroll employment down 20.5 million in 2020. TED: The economics daily (Blog), May 12, 2020*. Washington, DC: Bureau of Labor Statistics, U.S. Department of Labor.

Chandar, B., Gneezy, U., List, J. A., & Muir, I. (2019). *The drivers of social preferences: Evidence from a nationwide tipping field experiment (No. W26380)*. National Bureau of Economic Research.

Chetty, R., Friedman, J., Hendren, N., & Stepner, M. (2020). The economic impacts of COVID-19: Evidence from a new public database built from private sector data. *Opportunity Insights*.

CMAP (2015). *Chicago Community Area (CCA) CDS data*, https://datahub.cmap.illinois.gov/dataset/community-data-snapshots-raw-data/resource/8c4e096e-c90c-4bef-9cf1-9028d094296e. (Accessed 26 April 2021).

Conlisk, S. (2021). *Chicago Taxi Trips (Tipping), Mendeley Data*, V2. http://dx.doi.org/10.17632/tm47d7z5xf.2.

Crutsinger, M. (2021). *U.S. Economy shrank 3.5 percent in 2020 after growing 4 percent last quarter*. Associated Press, https://apnews.com.

Cunningham, Michael R (1979). Weather, mood, and helping behavior: quasi experiments with the sunshine samaritan.. *Journal of personality and social psychology*, *37*(11), 1947.

Ebesu Hubbard, A. S., Tsuji, A. A., Williams, C., & Seatriz, V., Jr. (2003). Effects of touch on gratuities received in same-gender and cross-gender dyads 1. *Journal of Applied Social Psychology*, *33*(11), 2427–2438.

Elliott, D., Tomasini, M., Oliveira, M., & Menezes, R. (2017). Tippers and stiffers: An analysis of tipping behavior in taxi trips. *Money*, *21*(22).

Engel, Ernst (1857). Die produktions- und consumtionsverhältnisse des königreichs sachsen. Zeitschrift des Statistischen Büreaus des Königlich Sächischen Ministeriums des Innern, 8 and 9. (Reprinted in Engel (1895). Appendix I, 1–54).

Exec. Order No. 43 (June 26, 2020).

Flynn, S. M., & Greenberg, A. E. (2012). Does weather actually affect tipping? An empirical analysis of time-series data 1. *Journal of Applied Social Psychology*, *42*(3), 702–716.

Frank, D. G., & Lynn, M. (2020). Shattering the illusion of the self-earned tip: The effect of a restaurant magician on co-workers' tips. *Journal of Behavioral and Experimental Economics*, *87*, Article 101560.

Galbadage, T., Peterson, B. M., & Gunasekera, R. S. (2020). Does COVID-19 spread through droplets alone? *Frontiers in Public Health*, *8*(163).

Greenberg, A. E. (2014). On the complementarity of prosocial norms: The case of restaurant tipping during the holidays. *Journal of Economic Behaviour and Organization*, *97*, 103–112.

Haggag, K., & Paci, G. (2014). Default tips. *American Economic Journal: Applied Economics*, *6*(3), 1–19.

Hershcovis, M. S., & Bhatnagar, N. (2017). When fellow customers behave badly: Witness reactions to employee mistreatment by customers. *Journal of Applied Psychology*, *102*(11), 1528.

Jin, D., Kim, K., & DiPietro, R. B. (2020). Workplace incivility in restaurants: Who's the real victim? Employee deviance and customer reciprocity. *International Journal of Hospitality Management*, *86*, Article 102459.

Kinder, M. (2021). *COVID-19's essential workers deserve hazard pay. Here's why—and how it should work*. Washington, DC: Brookings, https://www.brookings.edu.

[12] In fact, the pandemic has inspired a push for a policy of hazard pay. In April 2021 Senate Democrats introduced a proposal calling for a COVID-19 "Heroes Fund", through which the federal government would finance "premium pay" of an additional $25,000 (or roughly an additional $13 per hour) for essential frontline workers (Kinder, 2021).

Kuper-Smith, B. J., Doppelhofer, L. M., Oganian, Y., Rosenblau, G., & Korn, C. (2020). Optimistic beliefs about the personal impact of COVID-19.

Lee, W. K., & Sohn, S. Y. (2020). A large-scale data-based investigation on the relationship between bad weather and taxi tipping. *Journal of Environmental Psychology*, *70*, Article 101458.

Levy, J. (2021a). *Taxi Trips record data. Chicago Data Portal*, https://data.cityofchicago.org/Transportation/Taxi-Trips/wrvz-psew. (Accessed 9 April 2021).

Levy, J. (2021b). *Hospitalizations data. Chicago Data Portal*, https://data.cityofchicago.org/Health-Human-Services/COVID-19-Daily-Cases-Deaths-and-Hospitalizations/naz8-j4nc. (Accessed 14 May 2021).

Lynn, M. (2001). Restaurant tipping and service quality: A tenuous relationship. *Cornell Hotel and Restaurant Administration Quarterly*, *42*, 14–20.

Lynn, M. (2003). Tip levels and service: An update, extension and reconciliation. *Cornell Hotel and Restaurant Administration Quarterly*, *44*, 139–148.

Lynn, M. (2006). Tipping in restaurants and around the globe: An interdisciplinary review.

Lynn, M. (2009). Individual differences in self-attributed motives for tipping: Antecedents, consequences, and implications. *International Journal of Hospitality Management*, *28*(3), 432–438.

Lynn, M. (2015a). Service gratuities and tipping: A motivational framework. *Journal of Economic Psychology*, *46*, 74–88.

Lynn, M. (2015b). Explanations of service gratuities and tipping: Evidence from individual differences in tipping motivations and tendencies. *Journal of Behavioral and Experimental Economics*, *55*, 65–71.

Lynn, M. (2021). Did the COVID-19 pandemic dampen Americans' tipping for food services? Insights from two studies. *Compensation & Benefits Review*, *53*(3), 130–143.

Lynn, M., & Grassman, A. (1990). Restaurant tipping: an examination of three 'rational'explanations. *Journal of Economic Psychology*, *11*(2), 169–181.

Lynn, M., Jabbour, P., & Kim, W. G. (2012). Who uses tips as a reward for service and when? An examination of potential moderators of the service–tipping relationship. *Journal of Economic Psychology*, *33*(1), 90–103.

Lynn, M., & McCall, M. (2000). Gratitude and gratuity: a meta-analysis of research on the service-tipping relationship. *The Journal of Socio-Economics*, *29*(2), 203–214.

Lynn, M., & Sturman, M. C. (2003). It's simpler than it seems: an alternative explanation for the magnitude effect in tipping. *International Journal of Hospitality Management*, *22*(1), 103–110.

Lynn, Michael (2017). Should us restaurants abandon tipping? a review of the issues and evidence. *Psychosociological issues in human resource management*, *5*(1), 120–159.

Majid, K. A., Kolar, D. W., & Laroche, M. (2021). Support for small businesses during a health crisis. *Journal of Services Marketing*.

Mayo Clinic (2020). Early prediction of aggresive COVID-19 progression and hospitalization. https://www.mayo.edu/research/remote-monitoring-covid19-symptoms/people-with-covid19.

Parrett, M. (2006). An analysis of the determinants of tipping behavior: A laboratory experiment and evidence from restaurant tipping. *Southern Economic Journal*, *48*, 9–514.

Payscale (2012). How your tips impact outcomes. https://www.payscale.com/tipping-chart-2012.

Post, Peggy (1997). *Emily post's etiquette* (16th ed.). New York: William Morrow and Co.

Saraiva, C. (2020). *How a K-shaped recovery is widening U.S. inequality*. Washington Post, https://www.washingtonpost.com.

Saunders, S. G., & Lynn, M. (2010). Why tip? An empirical test of motivations for tipping car guards. *Journal of Economic Psychology*, *31*(1), 106–113.

Schwer, R. Keith., & Daneshvary, R. (2000). Tipping participation and expenditures in beauty salons. *Applied Economics*, *32*(15), 2023–2031.

Seiter, J. S. (2007). Ingratiation and gratuity: the effect of complimenting customers on tipping behavior in restaurants. *Journal of Applied Social Psychology*, *37*(3), 478–485.

Seiter, J. S., & Weger, H., Jr. (2013). Does a customer by any other name tip the same?: The effect of forms of address and customers' age on gratuities given to food servers in the United States. *Journal of Applied Social Psychology*, *43*(8), 1592–1598.

Star, N. (1988). *The international guide to tipping*. New York: Berkley Publishing Group.

Tan, W., & Zhang, J. (2020). Good days, bad days: Stock market fluctuation and taxi tipping decisions. *Management Science*.

Thaler, R., & Rosen, S. (1976). The value of saving a life: evidence from the labor market. In *Household production and consumption* (pp. 265–302). NBER.

Viscusi, W. K. (1978). Wealth effects and earnings premiums for job hazards. *The Review of Economics and Statistics*, *40*, 8–416.

Walster, E., Berscheid, E., & Walster, G. W. (1973). New directions in equity research. *Journal of Personality and Social Psychology*, *25*(2), 151.