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# The Economic Impact of Instacart on the U.S. Retail Grocery Industry Before and During the COVID-19 Pandemic

**Robert Kulick, Ph.D.**

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## About the Author

Dr. Kulick is an Associate Director in NERA's Communications, Media, and Internet Practice and an adjunct professor at George Mason University Law School.

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# Executive Summary

In recent years, the U.S. grocery industry has witnessed the development of several new technologies with the potential to transform how stores operate and interact with consumers. The COVID-19 pandemic rapidly increased the adoption of these new technologies as the industry simultaneously experienced a surge in demand and unprecedented operational challenges. Perhaps the most significant innovation in how grocery stores operate has been the advent of third-party delivery platforms led by Instacart.

Due to both the rapid expansion of Instacart and the potential for policy makers to enact regulatory changes at the local, state, or national level that may restrict or impair the operations of grocery delivery platforms, it is crucial to understand how Instacart affects grocery workers and the overall grocery industry. Thus, this study utilizes a series of rigorous statistical models to evaluate the relationship between Instacart adoption and economic outcomes in the U.S. retail grocery industry. Specifically, it examines three primary questions: (1) whether the positive relationship between Instacart adoption and economic growth in the grocery industry found in previous research for four states extends to all 50 states; (2) whether the surge in Instacart usage associated with the COVID-19 pandemic led directly to increased grocery employment and output; and (3) whether Instacart has had any impact on grocery workers' wages.

The statistical analysis presents strong evidence of a direct causal relationship between Instacart adoption and economic growth in the U.S. grocery industry. Both the pre-pandemic and post-pandemic results are based on the estimation of a series of distinct but complementary statistical models that differ in how Instacart adoption is measured. Thus, for ease of interpretation, the median estimates across models are reported in this executive summary. The results show:

- By the end of 2019, prior to the outbreak of COVID-19, Instacart was responsible for creating approximately 116,000 jobs in the U.S. grocery industry and for increasing grocery revenue by $2.9 billion.

- Instacart accounted for approximately 70 percent of pre-pandemic net grocery job creation from 2013 to 2019.

- During the pandemic, Instacart was responsible for creating approximately 70,000 additional jobs in the U.S. grocery industry and further annualized revenue growth of $3.5 billion. Thus, to date, Instacart has cumulatively created approximately 186,000 total jobs in the U.S. grocery industry and increased total annual grocery revenue by $6.4 billion.

- U.S. grocery employment surged during the pandemic, and approximately 92 percent of net grocery job creation associated with COVID-19 was attributable to Instacart.

- During the pandemic, Instacart increased average weekly wages for grocery workers by approximately $22 in markets served by Instacart.

- The consistency of the results across models and estimation strategies strongly supports a causal interpretation of the findings.

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# I. Introduction

In recent years, the U.S. grocery industry has witnessed the development of several new technologies with the potential to transform how stores operate and interact with consumers. The COVID-19 pandemic rapidly increased the adoption of these new technologies as the industry simultaneously experienced a surge in demand and unprecedented operational challenges.

Perhaps the most significant innovation in how grocery stores operate has been the advent of third-party delivery platforms led by Instacart. Starting with commercial service in San Francisco in early 2013, Instacart provides same-day delivery to customers from approximately 55,000 stores across the United States. From 2013 to 2019, Instacart expanded quickly with deliveries growing at a compound annual growth rate of 216 percent. During the COVID-19 pandemic, Instacart's already rapid growth accelerated dramatically with the value of transactions on the platform quadrupling.

Due to both the rapid expansion of Instacart and the potential for policy makers to enact regulatory changes at the local, state, or national level that may restrict or impair the operations of grocery delivery platforms, it is crucial to understand how Instacart affects grocery workers and the overall grocery industry. To date, rigorous statistical examination of Instacart's economic impact is limited to an analysis conducted by the author of the present study assessing Instacart's effect on grocery employment and output in four states.[1] The present study thus expands on the previous research by examining three primary questions regarding Instacart's effect on the grocery industry: (1) whether the positive relationship between Instacart adoption and grocery employment and output found in previous research extends to all 50 states;[2] (2) whether the surge in Instacart usage associated with the outbreak of COVID-19 enabled the growth of the grocery industry during the pandemic by directly increasing employment and output; and (3) whether Instacart has had any impact on the wages earned by grocery workers by, for instance, changing the composition of jobs within the industry or enhancing the ability of the industry to respond to changes in demand.

The results of this study demonstrate that the previously documented "Instacart Effect" is a national phenomenon, significantly increasing grocery employment and output within each major U.S. geographic region. The results also indicate that not only did the Instacart Effect persist during the COVID-19 pandemic, but that the relationship between Instacart adoption and economic growth in the grocery industry strengthened as large numbers of consumers opted for grocery delivery to avoid in-store shopping and replace restaurant dining.

Both the pre-pandemic and post-pandemic[3] results are based on the estimation of a series of distinct but complementary statistical models that differ in how Instacart adoption is measured.

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[1] Robert Kulick, *The Economic Impact of Instacart on the Retail Grocery Industry: Evidence from Four States*, NERA Economic Consulting (2020) (available at https://www.nera.com/publications/archive/2020/nera-economist-evaluates-the-economic-impact-of-instacart-on-the.html).

[2] The results reported throughout this study also include Washington, D.C.

[3] The terminology "post-pandemic" is used throughout this study to refer to the time period beginning in Q1 2020 when COVID-19 first appeared in the United States.

Thus, for ease of interpretation, the median estimates across models are reported below. The results show:

- By the end of 2019, prior to the outbreak of COVID-19, Instacart was responsible for creating approximately 116,000 jobs in the U.S. grocery industry and for increasing grocery revenue by $2.9 billion.

- Instacart accounted for approximately 70 percent of pre-pandemic net grocery job creation from 2013 to 2019.

- In Q2 2020, at the height of the COVID-19 pandemic, Instacart was responsible for creating approximately 70,000 additional jobs in the U.S. grocery industry and further annualized revenue growth of $3.5 billion. Thus, to date, Instacart has created approximately 186,000 total jobs in the U.S. grocery industry and increased total annual grocery revenue by $6.4 billion combining the pre- and post-pandemic economic impacts.

- U.S. grocery employment surged during the pandemic, and approximately 92 percent of net grocery job creation associated with COVID-19 was attributable to Instacart.

- By enabling the industry to respond to the surge in demand associated with the pandemic, Instacart increased average weekly wages for grocery workers by approximately $22 in markets served by Instacart. Furthermore, despite speculation that new technologies including third-party grocery delivery may change the composition of jobs within the industry favoring lower paying jobs,[4] the statistical results consistently show no reduction in average grocery wages associated with Instacart adoption pre-pandemic.

- There is strong evidence that the relationship between Instacart adoption and grocery employment, output, and wages is causal.

    - Multiple statistical techniques are used to rule out alternative explanations for the observed relationships. The consistency of the results across models and estimation strategies strongly supports a causal interpretation.

    - The evidence for a causal interpretation of the results is further supported by the application of a series of falsification or "placebo" tests to each model. These tests consistently show that the Instacart Effect is not a statistical artifact of broader trends in the retail economy, but rather reflects a specific relationship between Instacart adoption and economic outcomes in the U.S. grocery industry.

This study has two primary objectives. The first is to present the results of the underlying statistical analysis in a simple and straightforward manner to make the findings accessible to the general public. The second is to demonstrate the strength and consistency of the statistical results and the

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[4] See e.g., Francoise Carre and Chris Tilly, *Change and Uncertainty, Not Apocalypse: Technological Change and Store-Based Retail*, UC Berkeley Center for Labor Research (2020) (available at https://laborcenter.berkeley.edu/release-change-and-uncertainty-not-apocalypse-technological-change-and-store-based-retail/).

large amount of evidence supporting a causal interpretation of the findings through an in-depth discussion of the statistical methodology and data. For readers primarily interested in the first objective, the next section of this paper presents the key findings relying primarily on visualizations of the results with limited discussion of the underlying statistical methodology. The remaining sections provide an in-depth discussion of the data, models, estimation procedures, and econometric results.

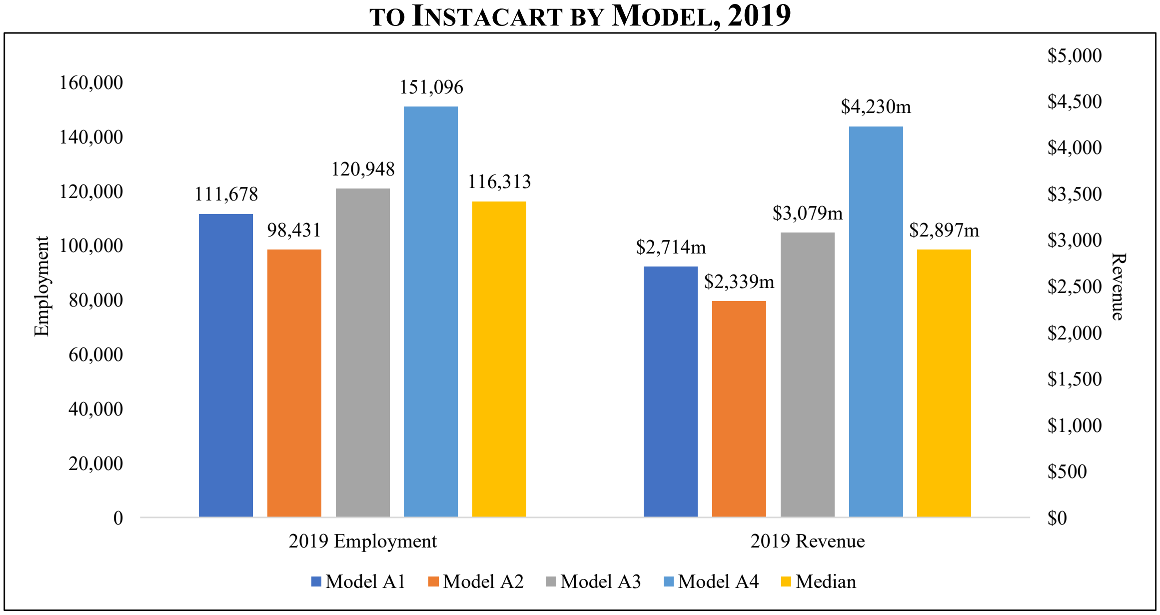
## II. Summary of Main Findings

The statistical analysis introduced in this study presents strong evidence that Instacart has driven and continues to propel significant increases in employment and output in the U.S. grocery industry. The first set of results presented below quantifies the economic growth experienced by the grocery industry due to Instacart's entry and adoption prior to the COVID-19 pandemic. The second set of results quantifies the incremental contribution of Instacart to the growth of the grocery industry during the pandemic.

### A. Pre-Pandemic Results

Figure 1 presents Instacart's contribution to grocery employment and revenue through 2019 based on estimates from four statistical models. The models, labeled A1-A4, differ in terms of how Instacart adoption is measured, and further details on the models are provided in the next section. The first four bars of each series represent the increase in grocery employment and revenue directly attributable to Instacart by model, and the fifth bar represents the median employment/revenue impact across models.

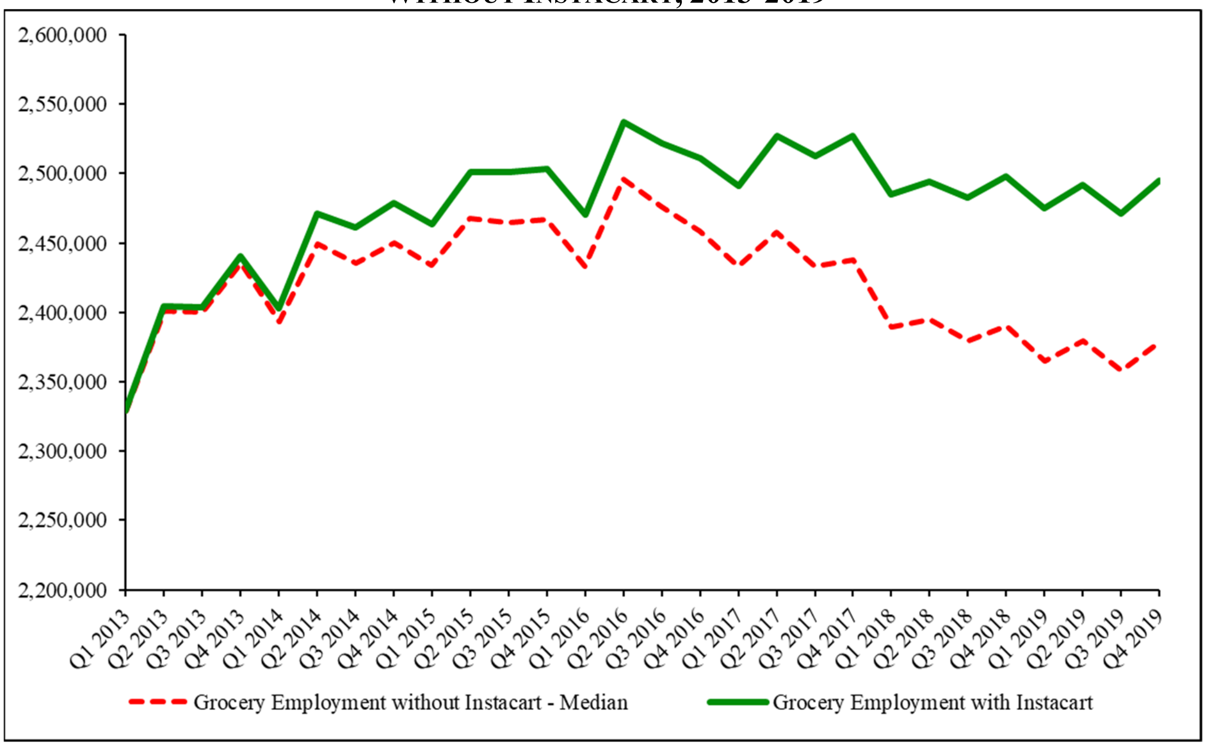
**FIGURE 1:**
**GROCERY EMPLOYMENT AND REVENUE ATTRIBUTABLE TO INSTACART BY MODEL, 2019**




For employment, the statistical results indicate that by the end of 2019, Instacart was responsible for creating 98,431 to 151,096 jobs in the U.S. grocery industry with a median estimate of 116,313 jobs. That is, in the absence of Instacart, there would have been 98,431 to 151,096 fewer grocery jobs in the United States in 2019. For output, the statistical results indicate that Instacart increased grocery revenue by \$2.3 billion to \$4.2 billion with a median estimate of \$2.9 billion, or that in the absence of Instacart, U.S. grocery stores would have earned \$2.3 billion to \$4.2 billion less in revenue in 2019.[5]

Figure 2 presents actual U.S. grocery employment from Q1 2013 to Q4 2019 (which includes employment growth attributable to Instacart) versus U.S. grocery employment without Instacart based on Instacart's median impact on grocery employment across the statistical estimates from models A1-A4.

**FIGURE 2:**
**U.S. GROCERY EMPLOYMENT WITH AND WITHOUT INSTACART, 2013-2019**




The top line depicts actual grocery employment in the United States since the commercial entry of Instacart into its first market and indicates that from Q1 2013 to Q4 2019, employment in the industry increased from 2,329,561 to 2,494,908, or 7.1 percent, representing net job creation of 165,347. In the absence of Instacart, however, the growth of the grocery industry would have been essentially stagnant. Without Instacart, the industry would have only grown by 49,369, a growth

[5] Because the underlying models are estimated on a quarterly basis, economic impacts for a given year are calculated based on Q4 employment and annualized revenue. Calculating revenue on an annualized basis allows for direct comparison of the pre-pandemic results, which are estimated for multiple quarters, and the post-pandemic results, which are estimated for a single quarter.

rate of 2.1 percent. Put differently, the statistical results indicate that Instacart accounted for approximately 70 percent of net grocery job creation from 2013 to 2019.

The results also indicate that the Instacart Effect is a national phenomenon fostering the growth of the grocery industry throughout the United States. Figures 3 and 4 present the median grocery employment and revenue increases attributable to Instacart by geographic region through 2019.

**FIGURE 3:**
**GROCERY EMPLOYMENT ATTRIBUTABLE TO INSTACART BY MODEL AND REGION, 2019**

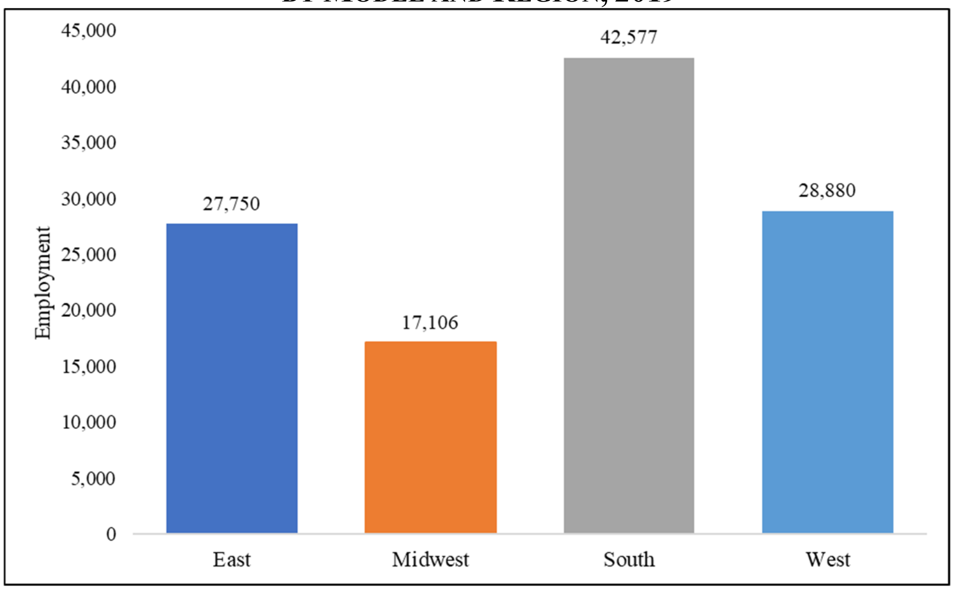
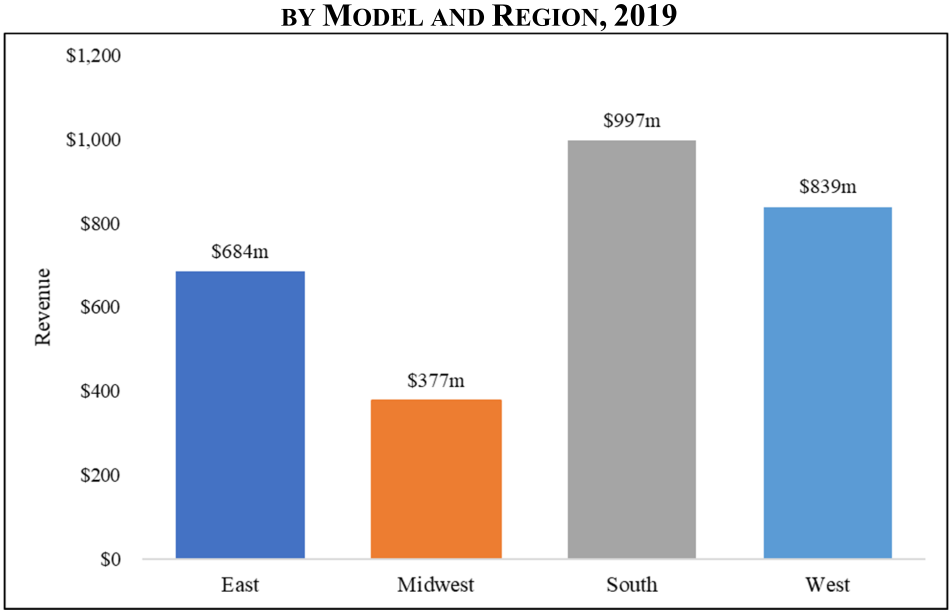



**FIGURE 4:**
**GROCERY REVENUE ATTRIBUTABLE TO INSTACART BY MODEL AND REGION, 2019**

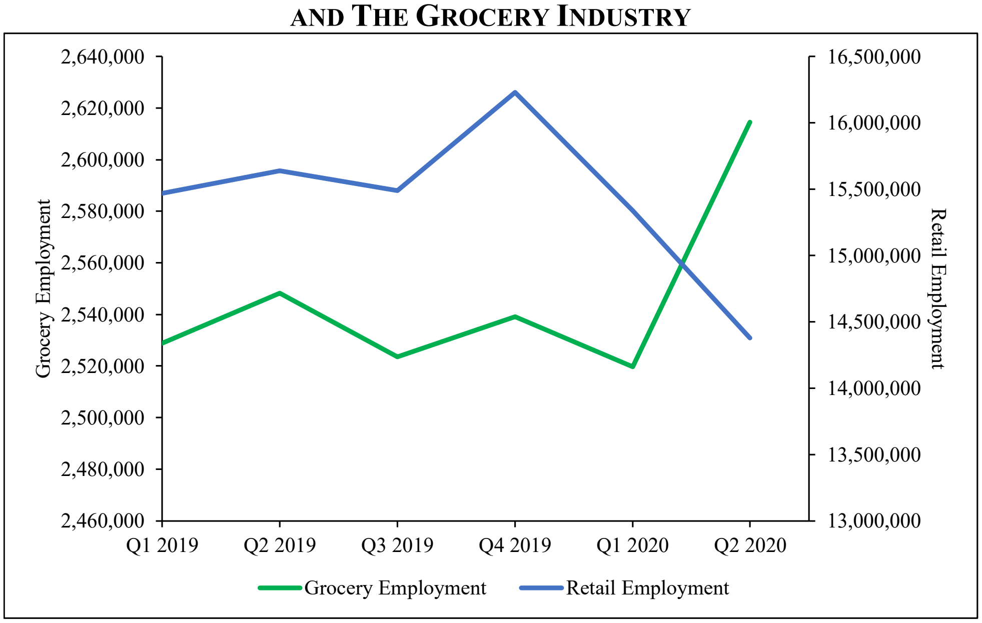


For employment, the models show that through 2019, Instacart created a median estimate of 27,750 jobs in the East;[6] 17,106 jobs in the Midwest;[7] 42,577 jobs in the South;[8] and, 28,880 jobs in the West.[9] For output, the models show that through 2019, Instacart increased grocery revenue by a median estimate of $684 million in the East; $377 million in the Midwest; $997 million in the South; and $839 million in the West.

## B. Post-Pandemic Results

The first cases of COVID-19 appeared in the United States early in Q1 2020, and, by the end of the quarter, much of the United States was subject to mandatory stay-at-home orders.[10] In Q2 2020, the disruption to the U.S. economy reached its peak as measured in terms of job losses. However, not all sectors of the economy declined. While the retail economy shed 1,853,762 jobs from Q4 2019 to Q2 2020, the U.S. grocery industry grew, adding 75,413 jobs over the same period. Instacart also grew dramatically during the pandemic with the value of transactions on the platform quadrupling. These economic shocks to the retail economy and the grocery industry are depicted in Figure 5.[11]

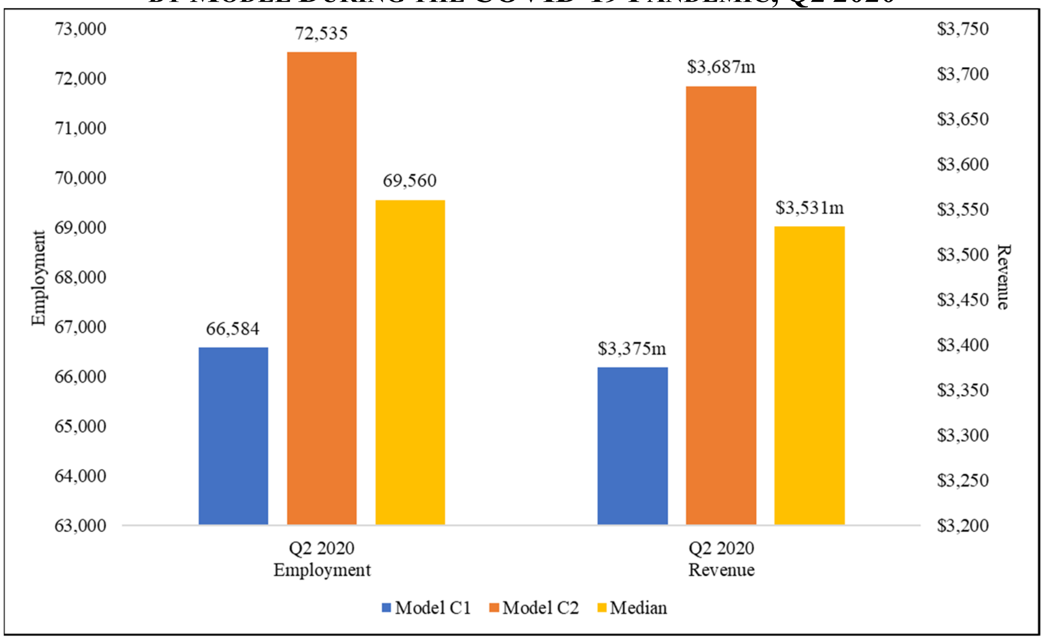
**FIGURE 5:**
**THE EFFECT OF THE COVID-19 PANDEMIC ON THE U.S. RETAIL ECONOMY AND THE GROCERY INDUSTRY**




[6] The East is defined as CT, MA, ME, NY, VT, DE, NH, NJ, RI, PA.
[7] The Midwest is defined as IA, IL, IN, KS, MI, MN, OH, WI, NE.
[8] The South is defined as AL, AR, FL, GA, KY, LA, MD, MO, MS, NC, OK, SC, TN, TX, VA, WV, DC.
[9] The West is defined as AZ, CA, CO, ID, MT, NM, NV, OR, UT, WA, ND, SD, WY, AK, HI.
[10] Anne Schuchat, "Public Health Response to the Initiation and Spread of Pandemic COVID-19 in the United States, February 24–April 21, 2020," *Morbidity and Mortality Weekly Report* (May 8, 2020) 551-556 (available at https://www.cdc.gov/mmwr/volumes/69/wr/mm6918e2.htm).
[11] Total grocery employment in Figure 5 for 2019 differs slightly from that reported in Figure 2 because Figure 2 is based on Census QWI data while Figure 5 is based on BLS QCEW data. As discussed below, the post-pandemic analysis is conducted using QCEW data as MSA-level QWI data are not yet available for Q2 2020.

Figure 6 presents the increase in grocery employment and revenue attributable to Instacart at the peak of the COVID-19 pandemic in Q2 2020. These effects are in addition to the impacts attributable to Instacart pre-pandemic. That is, the economic growth depicted in Figure 6 is incremental to the employment and revenue impacts presented in Figure 1. The models quantifying the magnitude of the Instacart Effect during the COVID-19 pandemic are labeled C1-C2 and are discussed in detail in the next section. The first two bars of each series represent the additional contribution of Instacart to grocery employment and revenue growth in Q2 2020 relative to Q4 2019 by model and the third bar represents the median employment/revenue impact across models.

**FIGURE 6:**
**GROCERY EMPLOYMENT AND REVENUE ATTRIBUTABLE TO INSTACART BY MODEL DURING THE COVID-19 PANDEMIC, Q2 2020**




For employment, the results indicate that Instacart created a further 66,584 to 72,535 jobs in the U.S. grocery industry during the pandemic with a median estimate of 69,560 jobs in addition to the jobs created by Instacart pre-pandemic. Thus, combining the employment results from Figure 1 and Figure 6, in the absence of Instacart, there would have been 165,015 to 223,631 fewer grocery jobs in the United States in Q2 2020. For revenue, the results indicate that Instacart increased grocery revenue by a further $3.4 billion to $3.7 billion with a median estimate of $3.5 billion. Again, combining the output results from Figure 1 and Figure 6, in the absence of Instacart, annualized grocery revenue would have been $5.7 billion to $7.9 billion lower in the United States in Q2 2020.

As shown in Figure 5, between Q4 2019 and Q2 2020, U.S. grocery employment increased by 75,413 jobs. Figure 7 uses models C1-C2 to quantify the proportion of the COVID-19 surge in U.S. grocery employment attributable to Instacart.

**FIGURE 7:**
**PERCENTAGE OF COVID-19 GROCERY EMPLOYMENT SURGE ATTRIBUTABLE TO INSTACART**

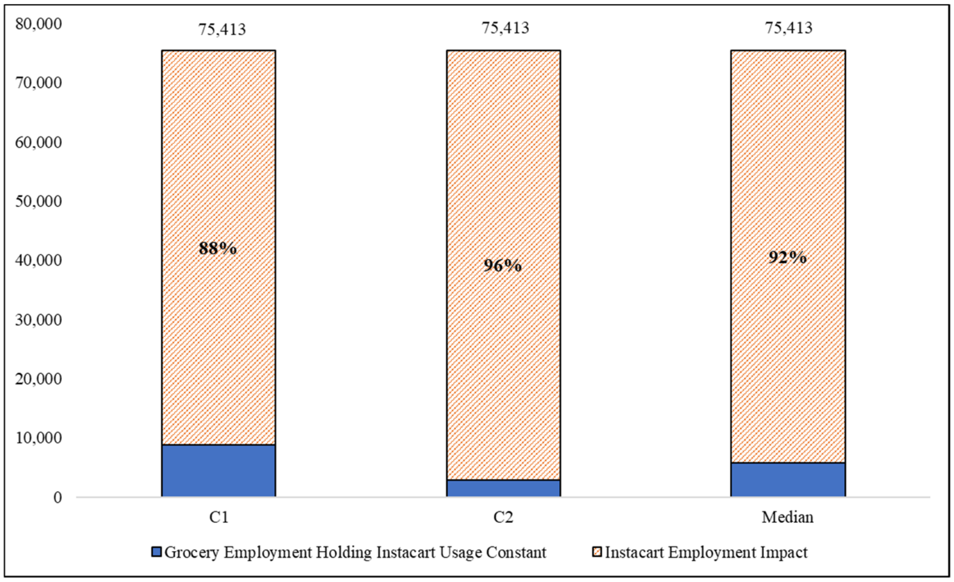
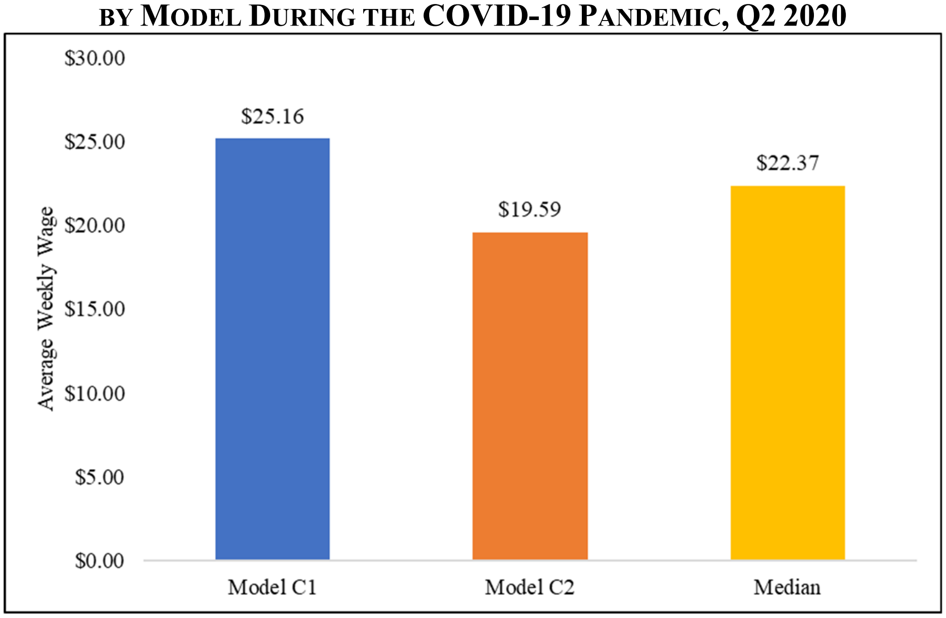



Figure 7 shows that 88 percent to 96 percent of the increase in grocery employment at the peak of the COVID-19 pandemic in Q2 2020 was attributable to Instacart with a median estimate of 92 percent.

For wages, Figure 8 shows that in markets it served, Instacart increased average weekly grocery wages by between $19.59 and $25.16 with a median estimate of $22.37 during the pandemic.

**FIGURE 8:**
**INCREASE IN AVERAGE GROCERY WAGE ATTRIBUTABLE TO INSTACART BY MODEL DURING THE COVID-19 PANDEMIC, Q2 2020**



Thus, during the pandemic, Instacart benefitted grocery workers by creating jobs and increasing wages and benefitted the grocery industry by increasing output. These gains stand in sharp contrast to the decline and disruption experienced by retailers and retail employees in other industries.

# III. Data and Methodology

## A. Overview

This study examines three primary questions regarding Instacart's effect on the U.S. retail grocery industry: (1) whether the positive relationship between Instacart adoption and economic growth in the grocery industry as measured by employment and output documented in Kulick (2020) extends to all 50 states; (2) whether the surge in Instacart usage catalyzed by the outbreak of COVID-19 directly enabled the growth of the grocery industry as measured by employment and output during the pandemic; and (3) whether Instacart has had any impact on grocery workers' wages by, for instance, changing the composition of jobs within the industry or enhancing the ability of the industry to respond to changes in demand. This study evaluates these questions using a statistical technique known as regression analysis. Regression analysis is a tool frequently used by economists to assess the relationship between two variables while holding constant other potential explanations for the observed relationship.

Instacart's effect on the grocery industry pre-pandemic is evaluated using a dataset combining internal sales data provided by Instacart with employment, payroll, and wage data from the U.S. Census Bureau Quarterly Workforce Indicators (QWI) program. Instacart's effect on the grocery industry post-pandemic is evaluated using a dataset combining Instacart's internal sales data with data from the U.S. Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages (QCEW).

To provide a rigorous assessment of whether there is evidence of a causal relationship between Instacart adoption and economic outcomes in the U.S. grocery industry, each question is evaluated using several regression models. Specifically, and as described in more detail below, the regression analyses are conducted using different measures of Instacart adoption in a local market. Furthermore, in estimating each model, multiple statistical techniques are used to rule out alternative explanations for the observed relationships. The consistency of the empirical results across models and statistical control strategies provides strong evidence of a causal relationship between Instacart adoption and economic growth in the U.S. grocery industry.

## B. Analysis of Instacart Entry and Adoption and Economic Outcomes in the U.S. Grocery Industry Pre-Pandemic

The economic impact of Instacart's entry and adoption on the U.S. grocery industry is quantified through the estimation of five regression models. The models use data on grocery employment, payroll, and average wages[12] in metropolitan statistical areas[13] (MSAs) across the 50 U.S. states and Washington, D.C. on a quarterly basis from Q1 2012 to Q4 2019 to evaluate the effect of Instacart on economic outcomes in the grocery industry. The starting point for the sample of Q1 2012 was chosen to capture a full year of data prior to Instacart's commercial entry into its first market, San Francisco, in Q1 2013. The end point represents the most recent quarter in which all variables used in the regression analysis have data available at a quarterly frequency.

Each of the five models uses a different measure of Instacart adoption. The first model (A1) quantifies Instacart adoption using the number of Instacart deliveries made in an MSA. The second model (A2) quantifies Instacart adoption using Instacart's total value of goods sold or GMV in an MSA. The third model (A3) quantifies Instacart adoption using the number of stores served by Instacart in an MSA. The fourth model (A4) quantifies Instacart adoption using the number of quarters following Instacart's entry into an MSA. The fifth model (A5) compares economic outcomes based on an indicator variable representing whether Instacart is present in the MSA. Because each measure of Instacart adoption utilized in models A1-A4 varies by quarter and is thus suitable for estimating the magnitude of the Instacart Effect at any given point in time, models A1-A4 are used to quantify Instacart's effect on grocery employment and output. Model A5 is included for comparison to the results from Kulick (2020) and as a robustness check supporting a causal interpretation of the results.

To rule out the possibility that the observed effects reflect spurious correlations due to unobserved factors, each model is estimated controlling for various fixed effects. In fixed-effects models, variation in the dependent variable resulting from unobserved factors is removed.[14] For instance, by controlling for MSA fixed effects in estimating models A1-A5, all MSA-level cross-sectional variation in the dependent variables is removed, and the estimation procedure eliminates the potential confounding effect of non-time varying characteristics specific to each MSA.[15] Similarly, controlling for year fixed effects eliminates potential bias from time trends encapsulated in the dependent variables. In addition to controlling for MSA and year effects, models A1-A5 also control for quarter and region-year interaction effects. Each model is estimated using the fixed-effects "within" estimator, and standard errors are clustered by state.

Further support for a causal interpretation of the results is provided by subjecting each of the primary regression models to six placebo tests. These placebo tests are designed to confirm that the statistical results reflect the specific relationship between Instacart adoption and economic outcomes in the grocery industry rather than a general correlation between Instacart adoption and broader trends in the retail economy. Thus, for the first five tests, each model is estimated replacing the dependent variable, employment in the grocery store industry, with employment in the book

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[12] The QWI MSA-level average wage data contain a small number of extreme outliers. Thus, observations from the QWI data with an average wage below the 0.1 percentile and above the 99.9 percentile are dropped from the regression sample.

[13] Approximately 98 percent of Instacart sales in Q4 2019 occurred in MSAs. Thus, because data for the variables used in the regression analysis are frequently missing for micropolitan areas, the regression sample is limited to MSAs.

[14] See e.g., James H. Stock and Mark W. Watson, *Introduction to Econometrics* (Boston: Pearson Education, 2003) at 278-279.

[15] See e.g., Fumio Hayashi, *Econometrics*, 1st ed. (Princeton, NJ and Oxford, U.K.: Princeton University Press, 2000) at 323-336.

store, sporting goods and hobby store, general merchandise store, furniture store, and clothing store industries. These placebo industries were selected as those most likely to be affected by retail demand shocks associated with the rise of e-commerce. For the sixth test, the model is estimated on total retail employment excluding employment from the grocery industry.

The underlying dataset used to estimate the Instacart entry and adoption models reflects the combination of data from three sources. Quarterly data indicating when Instacart started serving each MSA and other measures of Instacart adoption in an MSA were provided by Instacart. Quarterly employment, payroll, and average wage data by MSA are sourced from the U.S. Census Bureau's QWI program. Quarterly real gross domestic product (GDP) and data on population and personal income are sourced from the U.S. Bureau of Economic Analysis (BEA).[16] Yearly state-level data measuring personal expenditures on food and food services are also obtained from the BEA. Table 1 provides definitions of and sources for the variables used in the pre-pandemic Instacart entry and adoption regressions.

**TABLE 1:**
**VARIABLE DEFINITIONS AND SOURCES FOR INSTACART ENTRY AND ADOPTION ANALYSIS**

| Variables | Definition | Source |
|---|---|---|
| **Dependent** | | |
| log(Grocery Employment) | The natural logarithm of employment in the grocery stores industry (NAICS 4451) in a given MSA on the last day of a given quarter | U.S. Census Bureau |
| log(Grocery Payroll) | The natural logarithm of total payroll in the grocery stores industry (NAICS 4451) in a given MSA in a given quarter | U.S. Census Bureau |
| log(Grocery Wage) | The natural logarithm of average monthly earnings of full-quarter employees in the grocery stores industry (NAICS 4451) in a given MSA in a given quarter | U.S. Census Bureau |
| log(Book Store Employment) | The natural logarithm of employment in the book stores and news dealers industry (NAICS 4512) in a given MSA on the last day of a given quarter | U.S. Census Bureau |
| log(Sporting and Hobby Employment) | The natural logarithm of employment in the sporting goods, hobby, and musical instrument stores industry (NAICS 4511) in a given MSA on the last day of a given quarter | U.S. Census Bureau |
| log(General Merchandise Employment) | The natural logarithm of employment in the general merchandise stores, including warehouse clubs and supercenters, industry (NAICS 4523) in a given MSA on the last day of a given quarter | U.S. Census Bureau |
| log(Furniture Store Employment) | The natural logarithm of employment in the furniture stores industry (NAICS 4421) in a given MSA on the last day of a given quarter | U.S. Census Bureau |
| log(Clothing Store Employment) | The natural logarithm of employment in the clothing stores industry (NAICS 4481) in a given MSA on the last day of a given quarter | U.S. Census Bureau |
| log(Total Non-Grocery Retail Employment) | The natural logarithm of employment in all retail trade industries (NAICS 44-45) except the grocery stores industry (NAICS 4451) in a given MSA on the last day of a given quarter | U.S. Census Bureau |
| **Independent** | | |
| log(Deliveries) | The natural logarithm of the number of Instacart deliveries made in a given MSA in a given quarter | Instacart |
| log(GMV) | The natural logarithm of the Gross Merchandise Value of Instacart deliveries made in a given MSA in a given quarter | Instacart |
| log(Store Count) | The natural logarithm of the number of stores from which Instacart made deliveries in a given MSA in a given quarter | Instacart |
| log(Quarters Since Entry) | The natural logarithm of the number of quarters since the first quarter when Instacart Presence = 1 for a given MSA in a given quarter; Quarters Since Instacart Entry = 0 in first quarter of entry | Instacart |
| Instacart Presence | Indicator =1 if Instacart made deliveries in a given MSA in a given quarter | Instacart |
| log(Non-Grocery Employment) | The natural logarithm of employment in all industries except the grocery stores industry (NAICS 4451) in a given MSA on the last day of a given quarter | U.S. Census Bureau |
| Personal Income per Capita | Per capita personal income in a given MSA in a given year | U.S. BEA |
| log(GDP) | The natural logarithm of GDP in a given MSA in a given year | U.S. BEA |
| log(Consumer Expenditures on Food and Beverage Goods) | The natural logarithm of consumer expenditures on food and beverage goods in a given state in a given year | U.S. BEA |
| log(Consumer Expenditures on Food Services) | The natural logarithm of consumer expenditures on food services in a given state in a given year | U.S. BEA |

[16] The BEA provides county-level data which are mapped to the MSA-level Census QWI data.

Table 2 provides summary statistics for the variables used in the pre-pandemic Instacart entry and adoption analysis.

**TABLE 2:**
**SUMMARY STATISTICS FOR INSTACART**
**ENTRY AND ADOPTION ANALYSIS**

| Variables | Number of Observations | Mean | Median | Standard Deviation | Min | Max |
|---|---|---|---|---|---|---|
| **Primary Regression Variables** | | | | | | |
| Grocery Employment | 13,902 | 5,247 | 1,563 | 11,708 | 16 | 120,099 |
| Grocery Payroll | 13,980 | 33,444,702 | 8,881,609 | 81,476,113 | 51,341 | 1,037,489,961 |
| Grocery Wage | 13,931 | 1,186 | 1,138 | 285 | 404 | 3,348 |
| Store Count | 14,049 | 13 | 0 | 52 | 0 | 1,279 |
| Quarters Since Entry | 14,049 | 1.38 | 0.00 | 3.30 | 0.00 | 27.00 |
| Instacart Presence | 14,049 | 0.27 | 0.00 | 0.44 | 0.00 | 1.00 |
| Non-Grocery Employment | 13,846 | 274,862 | 86,904 | 611,717 | 1,049 | 6,481,660 |
| Personal Income per Capita (Annual) | 14,049 | 44,320 | 42,403 | 10,468 | 23,130 | 128,766 |
| GDP (Annual, Thousands) | 14,049 | 35,437,594 | 9,331,478 | 92,121,675 | 164,700 | 1,141,945,618 |
| Consumer Expenditures on Food and Beverage Goods (Annual, Millions) | 14,049 | 30,657 | 20,470 | 28,502 | 1,719 | 127,369 |
| Consumer Expenditures on Food Services (Annual, Millions) | 14,049 | 28,782 | 18,556 | 30,501 | 1,579 | 149,368 |
| **Placebo Regression Variables** | | | | | | |
| Book Store Employment | 11,313 | 220 | 83 | 453 | 0 | 5,095 |
| Sporting and Hobby Employment | 13,599 | 1,091 | 410 | 2,083 | 0 | 23,497 |
| General Merchandise Employment | 13,844 | 3,562 | 1,440 | 6,505 | 9 | 71,222 |
| Furniture Store Employment | 13,206 | 473 | 151 | 953 | 0 | 8,431 |
| Clothing Store Employment | 13,505 | 2,237 | 558 | 6,231 | 0 | 92,120 |
| Total Non-Grocery Retail Employment | 13,846 | 25,877 | 8,822 | 53,213 | 44 | 514,260 |

*Sources: See Table 1 sources. Note: The sample size of regression variables varies due to differences in data availability. Grocery wage data excludes observations with wage values below the 0.1 percentile and above the 99.9 percentile. Summary statistics for Deliveries and GMV are redacted.*

As indicated in Table 1, except for the Instacart Presence variable, the measures of Instacart adoption above are included in the regression analysis as the natural logarithm (log) of each variable. By taking the log of each variable, the regressions account for diminishing returns in the relationship between Instacart adoption and the dependent variables. The log function is also convenient as it allows the coefficients in the regression equations to be interpreted in percentage terms. However, because the dataset includes observations prior to Instacart's entry for each MSA and because the log function does not permit inclusion of zero-valued observations, each of the Instacart adoption variables is transformed by adding one to the variable so that the pre-entry value is equal to one rather than zero. To confirm the robustness of the analysis to this transformation, Appendix 1 presents alternative specifications where a range of root functions, which also account for diminishing returns but permit zero-valued observations, are applied to each measure of Instacart adoption instead. Appendix 1 shows that the results are robust to the use of these alternative specifications, and thus are not a statistical artifact created by the transformation of the Instacart adoption variables.

### C. Analysis of the Surge in Instacart Adoption and Economic Outcomes in the U.S. Grocery Industry During the COVID-19 Pandemic

The analysis described in this section assesses the relationship between the surge in Instacart adoption and economic outcomes in the grocery industry at the peak of the COVID-19 pandemic in Q2 2020. The statistical approach described in the previous section is adapted in three primary ways to address the distinct methodological considerations specific to investigating Instacart's economic impact on the grocery industry during the pandemic.

First, because of the rapid onset of the pandemic, the surge in Instacart adoption in Q2 2020 is most evident in a significant increase in deliveries and GMV. Thus, the models described in this section measure Instacart usage in terms of these two adoption variables.

Second, because the analysis is conducted for a cross-section of data at a point in time, it is not possible to use fixed effects to control for unobservables as in the pre-pandemic analysis. It remains crucial, however, to adequately control for demand conditions to support a causal interpretation of the results. In particular, because both grocery demand and Instacart adoption spike simultaneously in Q2 2020, it is important to adopt a control strategy to isolate the effect of Instacart adoption on grocery demand rather than grocery demand on Instacart adoption. Thus, in addition to applying controls for observable factors similar to those used in the pre-pandemic Instacart entry and adoption models, the analysis in this section also relies on a distinct set of statistical methodologies to control for potentially confounding factors.

As a starting point, each regression presented in this section controls directly for local COVID-19 cases and deaths to capture regional variation in the intensity of the pandemic. In addition, for the employment and output regressions, the dependent variables and the Instacart adoption variables for Q2 2020 are differenced relative to their pre-pandemic values in Q4 2019 to remove potentially spurious correlation due to unobserved pre-pandemic factors. Thus, the first of the post-pandemic statistical models (C1) evaluates the relationship between the change in grocery employment between Q2 2020 and Q4 2019 and the change in Instacart deliveries between Q2 2020 and Q4 2019. The second model (C2) evaluates the relationship between the change in grocery employment between Q2 2020 and Q4 2019 and the change in Instacart GMV between Q2 2020 and Q4 2019. Due to the absence of a potentially confounding secular trend in average grocery wages, for the average wage regressions, the levels of the dependent variables and Instacart adoption variables are used in estimating the models.

Finally, models C1 and C2 are estimated using a statistical technique known as instrumental variables (IV) estimation. While differencing the primary variables of interest and controlling for observable factors including the local intensity of the pandemic constitute effective strategies for controlling for local demand conditions, it is still useful to further rule out the possibility that a positive relationship between local grocery outcomes and Instacart adoption reflects high grocery demand related to the COVID-19 pandemic driving increased Instacart adoption. IV estimation proceeds by introducing an additional variable known as an "instrument" into the model that effects the independent variable of interest but is otherwise uncorrelated with unobserved factors that jointly determine the dependent variable and the independent variable.[17] In this case, using IV estimation to address the potential issue of simultaneity between grocery demand and Instacart adoption involves utilization of an instrument that is correlated with Instacart adoption but not correlated with COVID-19 related demand shocks except by facilitating Instacart adoption. The Quarters Since Entry variable employed directly as a regressor in the pre-pandemic Instacart entry

[17] See e.g., Jeffrey M. Wooldridge, *Econometric Analysis of Cross Section and Panel Data*, 2nd ed. (Cambridge, MA and London, U.K.: MIT press, 2010) at 89-96.

and adoption analysis is used as an instrument in estimating models C1 and C2 because it is highly correlated with increased Instacart adoption during the pandemic but, because it is fixed based on the date of Instacart's initial entry into a market, is not a function of current demand conditions.

Third, MSA-level QWI data is not yet available for Q2 2020. Thus, the post-pandemic statistical analysis uses employment, payroll,[18] and average wage data from the BLS' QCEW program. Unlike the QWI data, detailed industry-level data from QCEW are available at the county level rather than the MSA level. Accordingly, the county-level data from QCEW are mapped to MSAs as defined in the QWI data to maintain a consistent geographic scope between the pre- and post-pandemic analyses. To ensure privacy of employers and individuals, QCEW data are sometimes redacted based on data disclosure guidelines set by regional government agencies that collect labor statistics.[19] Data redaction is likely to occur when, for a given industry, the number of employers in a county is small, or when a single firm makes up a large proportion of the county's employment, in which cases, the redacted data could be used to make inferences regarding individual employers.[20] As such, the missingness of data may not be random, but may depend on systematic factors. Failing to consider the structure of missingness in the data can therefore lead to bias in the statistical estimates.

A statistical technique known as inverse propensity score weighting is thus used to address the potential for sample selection bias to affect the statistical results.[21] Specifically, the propensity of inclusion (the probability of the data being present) is first estimated using county-specific independent variables including population, personal income, GDP, population density, and region. Observations in the dataset are then weighted by the inverse of this propensity metric in estimating the regression models, controlling for potential sample selection bias. All regression results deriving from the post-pandemic statistical models presented in Section V are propensity score weighted.[22] However, the results are similar without propensity score weighting. The similarity of the results with and without propensity score weighting indicates that sample selection bias does not present a concern.

Table 3 provides definitions and sources of variables used in the post-pandemic analysis.

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[18] A variable identical to QWI's payroll variable is not available in the QCEW. However, the QCEW wages variable captures similar information: "QCEW wages data represent the total compensation paid during the calendar quarter, regardless of when the services were performed." See Quarterly Census of Employment and Wages, QCEW Overview (available at https://www.bls.gov/cew/overview.htm).

[19] Quarterly Census of Employment and Wages, QCEW Overview (available at https://www.bls.gov/cew/overview.htm).

[20] See e.g., Kentucky Center for Statistics, Kentucky Industry Profiler Technical Notes (2018) (available at https://kcews.ky.gov/Content/Reports/Industry%20profiler%20tech%20notes.pdf).

[21] See e.g., John Haltiwanger, Ron S. Jarmin, Robert Kulick, and Javier Miranda, "High Growth Young Firms: Contribution to Job, Output, and Productivity Growth," *Measuring Entrepreneurial Businesses: Current Knowledge and Challenges* (University of Chicago Press, 2017) 11-62 at 17.

[22] While QWI data are also sometimes redacted, only a small number of observations in the pre-pandemic regression sample are missing. Out of the 440 MSAs in the QWI data, only one MSA is missing from the sample for the entirety of the sample period, and out of all MSA-quarter observations in the dataset, fewer than two percent of observations are missing. Thus, no adjustment is necessary for the pre-pandemic Instacart entry and adoption regressions.

## TABLE 3:
## VARIABLE DEFINITIONS AND SOURCES FOR COVID-19 ANALYSIS

| Variables | Definition | Source |
|---|---|---|
| **Dependent** | | |
| log(Grocery Employment) (Q4 2019-Q2 2020) | The difference in the natural logarithm of employment in the grocery stores industry (NAICS 4451) in a given county between Q4 2019 and Q2 2020 | U.S. BLS |
| log(Grocery Payroll) (Q4 2019-Q2 2020) | The difference in the natural logarithm of total wages in the grocery stores industry (NAICS 4451) in a given county between Q4 2019 and Q2 2020 | U.S. BLS |
| log(Grocery Average Weekly Wage Q2 2020) | The natural logarithm of average weekly wage in the grocery stores industry (NAICS 4451) in a given county in Q2 2020 | U.S. BLS |
| log(Book Store Employment) (Q4 2019-Q2 2020) | The difference in the natural logarithm of employment in the book stores and news dealers industry (NAICS 4512) in a given county between Q4 2019 and Q2 2020 | U.S. BLS |
| log(Sporting and Hobby Employment) (Q4 2019-Q2 2020) | The difference in the natural logarithm of employment in the sporting goods, hobby, and musical instrument stores industry (NAICS 4511) in a given county between Q4 2019 and Q2 2020 | U.S. BLS |
| log(General Merchandise Employment) (Q4 2019-Q2 2020) | The difference in the natural logarithm of employment in the general merchandise stores, including warehouse clubs and supercenters, industry (NAICS 4523) in a given county between Q4 2019 and Q2 2020 | U.S. BLS |
| log(Furniture Store Employment) (Q4 2019-Q2 2020) | The difference in the natural logarithm of employment in the furniture stores industry (NAICS 4421) in a given county between Q4 2019 and Q2 2020 | U.S. BLS |
| log(Clothing Store Employment) (Q4 2019-Q2 2020) | The difference in the natural logarithm of employment in the clothing stores industry (NAICS 4481) in a given county between Q4 2019 and Q2 2020 | U.S. BLS |
| log(Total Non-Grocery Retail Employment) (Q4 2019-Q2 2020) | The difference in the natural logarithm of employment in all retail trade industries (NAICS 44-45) except the grocery stores industry (NAICS 4451) in a given county between Q4 2019 and Q2 2020 | U.S. BLS |
| **Independent** | | |
| log(Deliveries) (Q4 2019-Q2 2020) | The diffference in the natural logarithm of the number of Instacart deliveries made in a given county between Q4 2019 and Q2 2020 | Instacart |
| log(GMV) (Q4 2019-Q2 2020) | The difference in the natural logarithm of the Gross Merchandise Value of Instacart deliveries made in a given county between Q4 2019 and Q2 2020 | Instacart |
| log(Deliveries Q2 2020) | The natural logarithm of the number of Instacart deliveries made in a given county in Q2 2020 | Instacart |
| log(GMV Q2 2020) | The natural logarithm of the Gross Merchandise Value of Instacart deliveries made in a given county in Q2 2020 | Instacart |
| log(Non-Grocery Employment) (Q4 2019- Q2 2020) | The difference in the natural logarithm of employment in all industries except the grocery stores industry (NAICS 4451) in a given county between Q4 2019 and Q2 2020 | U.S. BLS |
| log(Non-Grocery Employment Q2 2020) | The natural logarithm of employment in all industries except the grocery stores industry (NAICS 4451) in a given county on the last day in Q2 2020 | U.S. BLS |
| Population Density | Population density in a given county: population (BEA) in 2019 divided by land area in 2010 (U.S. Census Bureau) | U.S. BEA & U.S. Census Bureau |
| Personal Income per Capita | Per capita personal income in a given county in 2019 | U.S. BEA |
| log(GDP) | The natural logarithm of GDP in a given county in 2019 | U.S. BEA |
| COVID Cases per Capita Q2 2020 | Average COVID-19 cases per day in a given county over Q2 2020 | New York Times COVID-19 Data |
| COVID Deaths per Capita Q2 2020 | The total number of deaths from COVID-19 in a given county in Q2 2020 | New York Times COVID-19 Data |

As with the pre-pandemic Instacart entry and adoption analysis, Instacart adoption during the pandemic in a county is included in the regression analysis as the log of the relevant variable. So that counties without Instacart can be included in the analysis, the Instacart adoption variables are again transformed by adding one to the value of each variable. Appendix 1 presents the results for models C1-C2 where root functions are again used as alternatives to the log specification and shows that the statistical results are highly robust. Table 4 provides summary statistics.

**TABLE 4:**
**SUMMARY STATISTICS FOR**
**COVID-19 ANALYSIS**

| Variables | Number of Observations | Mean | Median | Standard Deviation | Min | Max |
|---|---|---|---|---|---|---|
| **Primary Regression Variables** | | | | | | |
| Grocery Employment (Q4 2019-Q2 2020) | 852 | 76 | 30 | 280 | -2,942 | 2,411 |
| Grocery Payroll (Q4 2019-Q2 2020) | 852 | 1,693,657 | 660,875 | 4,604,908 | -30,583,082 | 69,386,338 |
| Grocery Average Weekly Wage Q2 2020 | 879 | 508 | 499 | 97 | 266 | 991 |
| Non-Grocery Employment (Q4 2019- Q2 2020) | 851 | -14,439 | -3,992 | 39,111 | -632,428 | 15,496 |
| Non-Grocery Employment Q2 2020 | 879 | 107,860 | 41,583 | 220,310 | 253 | 3,295,986 |
| Personal Income per Capita (Annual) | 1,159 | 49,255 | 46,441 | 14,239 | 23,081 | 197,847 |
| GDP (Annual, Thousands) | 1,159 | 14,626,056 | 4,124,397 | 42,113,151 | 40,209 | 726,943,301 |
| Population Density (Persons per Square Mile) | 1,159 | 623 | 160 | 2,875 | 1 | 71,341 |
| COVID Cases per Capita Q2 2020 | 1,159 | 0.003 | 0.002 | 0.005 | 0.000 | 0.084 |
| COVID Deaths per Capita Q2 2020 | 1,159 | 0.013 | 0.005 | 0.024 | 0.000 | 0.269 |
| **Placebo Regression Variables** | | | | | | |
| Book Store Employment (Q4 2019-Q2 2020) | 398 | -97 | -57 | 151 | -1,752 | 369 |
| Sporting and Hobby Employment (Q4 2019-Q2 2020) | 472 | -219 | -105 | 345 | -3,222 | 161 |
| General Merchandise Employment (Q4 2019-Q2 2020) | 744 | 4 | 9 | 353 | -5,200 | 2,734 |
| Furniture Store Employment (Q4 2019-Q2 2020) | 607 | -58 | -19 | 122 | -1,369 | 296 |
| Clothing Store Employment (Q4 2019-Q2 2020) | 733 | -643 | -227 | 1,576 | -23,062 | 151 |
| Total Non-Grocery Retail Employment (Q4 2019-Q2 2020) | 852 | -2,142 | -692 | 5,132 | -80,950 | 878 |

*Sources: See Table 3 sources. Note: The sample size of regression variables varies due to differences in data availability. Summary statistics for Deliveries and GMV are redacted.*

# IV. Statistical Estimation of the Pre-Pandemic Instacart Entry and Adoption Models

## A. Employment Effects of Instacart Entry and Adoption

This section begins with estimation of the primary statistical models relating retail grocery employment to Instacart adoption by MSA from Q1 2012 to Q4 2019. The dependent variable for each model A1-A5 is (log) grocery employment and the independent variables of interest are the five measures of Instacart adoption discussed in the previous section: (log) Deliveries, GMV, Stores, Quarters Since Entry and Instacart Presence. The results are presented in Table 5.

**TABLE 5:**
**GROCERY EMPLOYMENT**
**REGRESSION MODEL ESTIMATES**

| **VARIABLES** | **A1** | **A2** | **A3** | **A4** | **A5** |
|---|---|---|---|---|---|
| log(Deliveries) | 0.004*** | | | | |
| log(GMV) | | 0.003*** | | | |
| log(Store Count) | | | 0.011*** | | |
| log(Quarters Since Entry) | | | | 0.026*** | |
| Instacart Presence | | | | | 0.027*** |
| log(Non-Grocery Employment) | 0.493*** | 0.496*** | 0.491*** | 0.493*** | 0.505*** |
| Personal Income per Capita | -0.001 | -0.001 | -0.002* | -0.002** | -0.001 |
| log(GDP) | 0.057 | 0.057 | 0.060 | 0.054 | 0.059 |
| log(Consumer Expenditures on Food and Beverage Goods) | 0.136 | 0.143 | 0.132 | 0.126 | 0.158 |
| log(Consumer Expenditures on Food Services) | 0.146 | 0.148 | 0.150 | 0.134 | 0.154 |
| Constant | -1.741 | -1.863 | -1.753 | -1.458 | -2.220 |
| Observations | 13,846 | 13,846 | 13,846 | 13,846 | 13,846 |
| R-squared | 0.148 | 0.148 | 0.148 | 0.151 | 0.146 |
| Number of MSAs | 439 | 439 | 439 | 439 | 439 |
| MSA Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Quarter Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Region-Year Fixed Effects | Yes | Yes | Yes | Yes | Yes |

*Sources: See Table 1 sources. [1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level. [4] All regressions have robust standard errors clustered by state.*

As indicated in Table 5, each regression controls for total MSA-level employment excluding grocery employment, personal income per capita, real GDP, state-level consumer expenditures on food and beverage goods, and state-level consumer expenditures on food services. Each regression includes 439 MSAs across the 50 U.S. states and Washington, D.C. The R-squared value represents the "within" R-squared, and standard errors are clustered by state.

For models A1-A4, the coefficient estimates on the Instacart adoption variables in Table 5 can be interpreted as the percentage change in grocery employment due to a one percent increase in Instacart adoption. The results for model A1 indicate that a one percent increase in Instacart deliveries in an MSA, all else equal, increases grocery employment by 0.004 percent. The results for model A2 indicate that a one percent increase in Instacart GMV increases grocery employment by 0.003 percent. The results for model A3 indicate that a one percent increase in the number of stores served by Instacart in an MSA increases grocery employment by 0.011 percent. The results for model A4 indicate that a one percent increase in the number of quarters since Instacart's entry into an MSA is associated with a 0.026 percent increase in grocery employment. The results for model A5 indicate that, abstracting from the duration of Instacart's presence in an MSA or the intensity of Instacart use, Instacart entry is associated on average with a 2.7 percent increase in grocery employment. For all five models, the coefficients on the Instacart adoption variables are statistically significant.

To test whether the relationship between Instacart adoption and grocery employment is consistent in direction and magnitude across different regions of the United States, in Table 6, the regressions from Table 5 are re-estimated allowing all coefficients in the model to vary by region. The variables of interest are the Instacart adoption terms interacted with variables representing the major geographic regions of the United States.

**TABLE 6:**
**GROCERY EMPLOYMENT**
**REGRESSION MODEL ESTIMATES BY REGION**

| VARIABLES | A1 | A2 | A3 | A4 | A5 |
|---|---|---|---|---|---|
| log(Deliveries) | 0.004*** | | | | |
| log(Deliveries) * South | 0.001 | | | | |
| log(Deliveries) * West | -0.001 | | | | |
| log(Deliveries) * Midwest | 0.000 | | | | |
| log(GMV) | | 0.002*** | | | |
| log(GMV) * South | | 0.001 | | | |
| log(GMV) * West | | -0.001 | | | |
| log(GMV) * Midwest | | 0.000 | | | |
| log(Store Count) | | | 0.010*** | | |
| log(Store Count) * South | | | 0.002 | | |
| log(Store Count) * West | | | -0.003 | | |
| log(Store Count) * Midwest | | | 0.002 | | |
| log(Quarters Since Entry) | | | | 0.023*** | |
| log(Quarters Since Entry) * South | | | | 0.013 | |
| log(Quarters Since Entry) * West | | | | -0.010 | |
| log(Quarters Since Entry) * Midwest | | | | -0.001 | |
| Instacart Presence | | | | | 0.021** |
| Instacart Presence * South | | | | | 0.012 |
| Instacart Presence * West | | | | | -0.001 |
| Instacart Presence * Midwest | | | | | -0.001 |

*Sources: See Table 1 sources. [1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level. [4] All regressions have robust standard errors clustered by state.*

In these regressions, the uninteracted Instacart adoption variable represents the effect in the East and the coefficients on the regional interaction variables represent the difference between the magnitude of the coefficient in the East and the coefficient in the specified region.[23] That is, the magnitude of the Instacart Effect in the South for each model is the sum of the coefficient on the uninteracted Instacart adoption variable and the coefficient on the interaction of the Instacart adoption variable and an indicator variable for the South. Specifying the models in this way allows for a direct test of whether the regional differences are statistically significant based on the individual coefficients of the regional interaction variables. Across all five models, there are no statistically significant differences across regions. These results support two conclusions: (1) that the Instacart Effect is a national phenomenon, and (2) that it is reasonable to use the pooled (non-regional) Instacart adoption coefficients estimated in Table 5 for the purposes of quantifying the economic impacts generated by Instacart both nationally and locally. Thus, the regional economic impacts presented in Figures 3 and 4 in Section II are calculated using the pooled coefficient estimates from Table 5.

To provide further evidence for a causal interpretation of the results, each model is subjected to six placebo tests. For these tests, each model is estimated by replacing the dependent variable, grocery industry employment, with employment in the book store, sporting goods and hobby store,

[23] Because the models in Table 6 are estimated with regional interaction terms for all variables including the controls, the coefficient estimates reported above are independent of which region is chosen as the base category.

general merchandise store, furniture store, clothing store industries and non-grocery retail industries. Table 7 displays the estimated model coefficients for each of the placebo tests.

**TABLE 7:**
**PLACEBO TEST RESULTS**
**BY INDUSTRY**

| Models | log(Book Store Employment) | log(Sporting Goods Store Employment) | log(General Merchandise Store Employment) | log(Furniture Store Employment) | log(Clothing Store Employment) | log(Non-Grocery Retail Employment) |
|---|---|---|---|---|---|---|
| A1 | 0.002 | -0.009*** | 0.001 | 0.003 | -0.003 | -0.001 |
| A2 | 0.001 | -0.005*** | 0.001 | 0.002 | -0.002 | -0.000 |
| A3 | 0.003 | -0.024*** | 0.003 | 0.009 | -0.007 | -0.001 |
| A4 | 0.003 | -0.047*** | 0.008 | 0.012 | -0.010 | -0.003 |
| A5 | 0.004 | -0.035** | 0.001 | 0.012 | -0.012 | -0.002 |

*Sources: See Table 1 sources. [1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level. [4] All regressions have robust standard errors clustered by state.*

Systematic evidence of false positives from the placebo tests would potentially raise concern that the positive relationship between Instacart adoption and grocery employment could reflect the effect of aggregate retail demand shocks or retail demand shocks related to the growth of e-commerce. However, as shown in Table 7, there are no statistically significant false positives, much less a systematic pattern of false positives. Indeed, the only statistically significant results in Table 7 are the negative results for the sporting goods and hobby store industry, and as shown in Table 11 below, the placebo tests conducted in Section V for this industry lose statistical significance. Thus, the placebo tests confirm that the regression results reflect the specific relationship between Instacart adoption and employment in the grocery industry rather than a relationship between Instacart's growth and broader trends in the retail economy.

Figure 9 presents the increase in grocery employment attributable to Instacart based on the statistical estimates from Table 5 from Q1 2013 to Q4 2019. Each model indicates steady growth over time with the pace accelerating in 2017 due to the entry of Instacart into an increasing number of markets. By the end of 2013, the median estimate of the number of grocery jobs created by Instacart was 5,099; by the end of 2014, the median estimate of the number of grocery jobs created by Instacart was 28,448; by the end of 2015, the median estimate of the number of grocery jobs created by Instacart was 36,256; by the end of 2016, the median estimate of the number of grocery jobs created by Instacart was 52,537; by the end of 2017, the median estimate of the number of grocery jobs created by Instacart was 89,377; by the end of 2018, the median estimate of the number of grocery jobs created by Instacart was 107,922; by the end of 2019, the median estimate of the number of grocery jobs created by Instacart was 116,313 as also indicated in Figure 1 in Section II.

**FIGURE 9:**
**GROCERY EMPLOYMENT ATTRIBUTABLE TO INSTACART BY MODEL, 2013-2019**

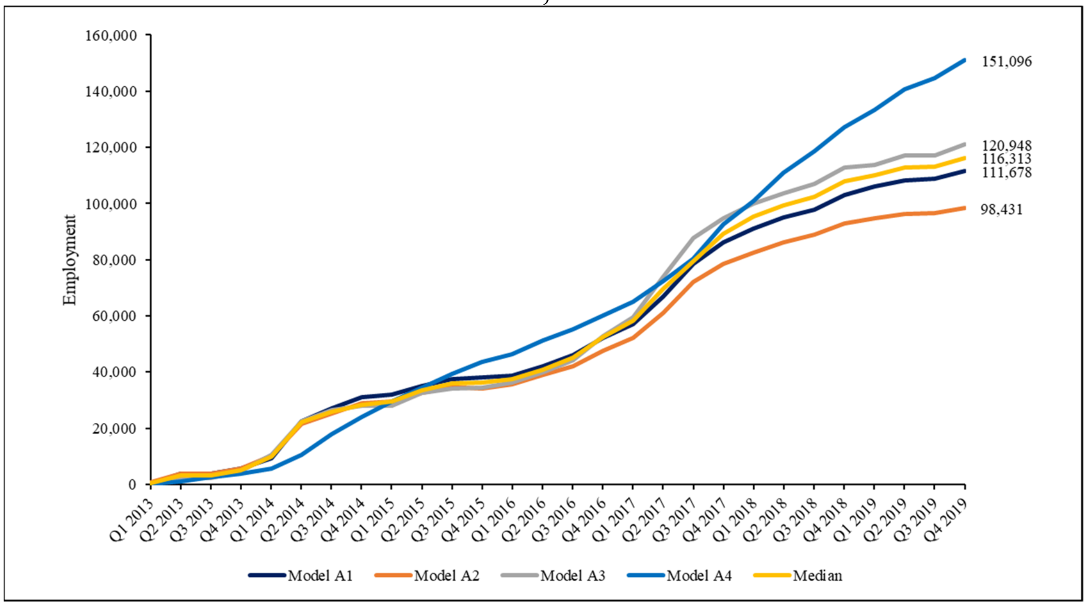
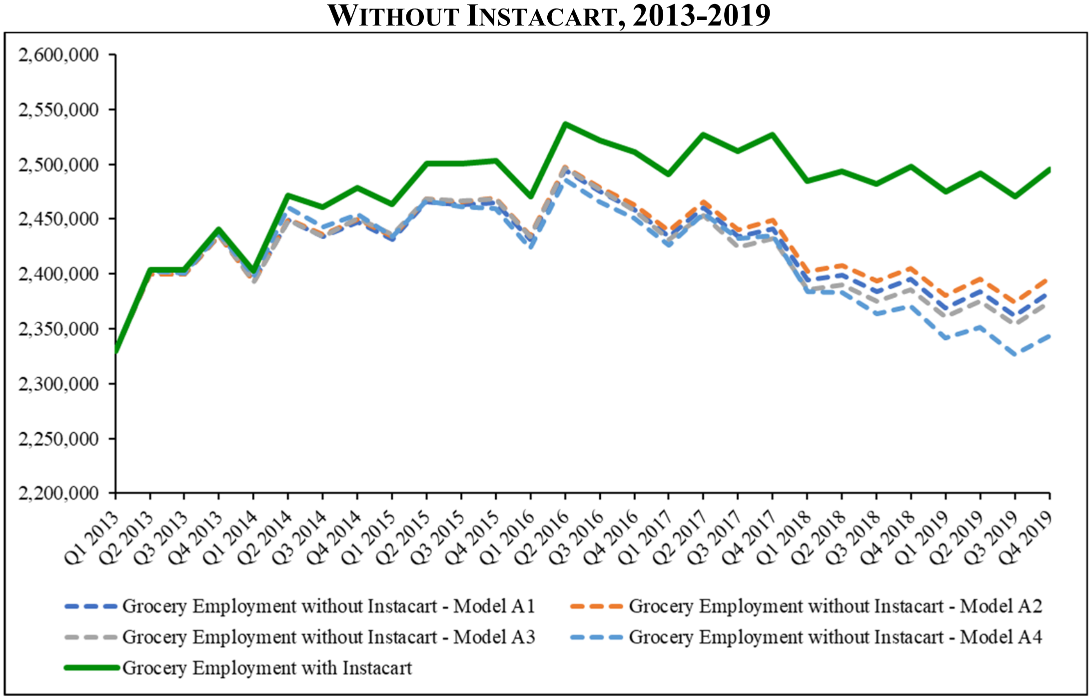



Figure 10 presents actual U.S. grocery employment from Q1 2013 to Q4 2019 versus U.S. grocery employment without Instacart based on the results of models A1-A4.

**FIGURE 10:**
**U.S. GROCERY EMPLOYMENT WITH AND WITHOUT INSTACART, 2013-2019**



As discussed in Section II, from 2013 to 2019, employment in the grocery industry increased from 2,329,561 to 2,494,908 (7.1 percent) representing net job creation of 165,347. Figure 10 shows that without Instacart, the grocery industry would have only grown by 0.6 percent to 2.9 percent, and that net job creation would have been only a fraction of its actual level with estimates ranging from 14,251 to 67,550. That is, the statistical results indicate that Instacart accounted for 60 to 91 percent of net grocery job creation from 2013 to 2019. The median grocery employment estimates without Instacart in Figure 2 in Section II are based on the results depicted in Figure 10.

## B. Output Effects of Instacart Entry and Adoption

From economic theory, it can be inferred that the increases in grocery employment attributable to Instacart are a consequence of an increase in the marginal revenue product of grocery workers.[24] Thus, following the methodology outlined in Kulick (2020), in this section grocery payroll is used as a proxy for output to provide lower bound estimates of the increase in grocery revenue attributable to Instacart. The results represent lower bound estimates as they abstract from factors such as profits and expenditures on intermediate factors of production such as materials.

Table 8 presents the grocery revenue models using payroll as the dependent variable to estimate the increase in grocery revenue attributable to Instacart. The magnitudes of the effects and the pattern of statistical significance are similar to the employment regressions presented in Table 5.

**TABLE 8:**
**GROCERY REVENUE**
**REGRESSION MODEL ESTIMATES**

| VARIABLES | A1 | A2 | A3 | A4 | A5 |
|---|---|---|---|---|---|
| log(Deliveries) | 0.004*** | | | | |
| log(Adjusted GMV) | | 0.002*** | | | |
| log(Store Count) | | | 0.009*** | | |
| log(Quarters Since Entry) | | | | 0.024*** | |
| Instacart Presence | | | | | 0.021*** |
| log(Non-Grocery Employment) | 0.524*** | 0.527*** | 0.522*** | 0.521*** | 0.535*** |
| Personal Income per Capita | -0.001 | -0.001 | -0.001 | -0.002 | -0.001 |
| log(GDP) | 0.076 | 0.076 | 0.078 | 0.072 | 0.078 |
| log(Consumer Expenditures on Food and Beverage Goods) | 0.241 | 0.247 | 0.237 | 0.227 | 0.260 |
| log(Consumer Expenditures on Food Services) | 0.146 | 0.147 | 0.148 | 0.131 | 0.153 |
| Constant | 5.095*** | 4.982*** | 5.119*** | 5.510*** | 4.683** |
| Observations | 13,846 | 13,846 | 13,846 | 13,846 | 13,846 |
| R-squared | 0.311 | 0.311 | 0.311 | 0.313 | 0.310 |
| Number of MSAs | 439 | 439 | 439 | 439 | 439 |
| MSA Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Quarter Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Region-Year Fixed Effects | Yes | Yes | Yes | Yes | Yes |

*Sources: See Table 1 sources. [1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level. [4] All regressions have robust standard errors clustered by state.*

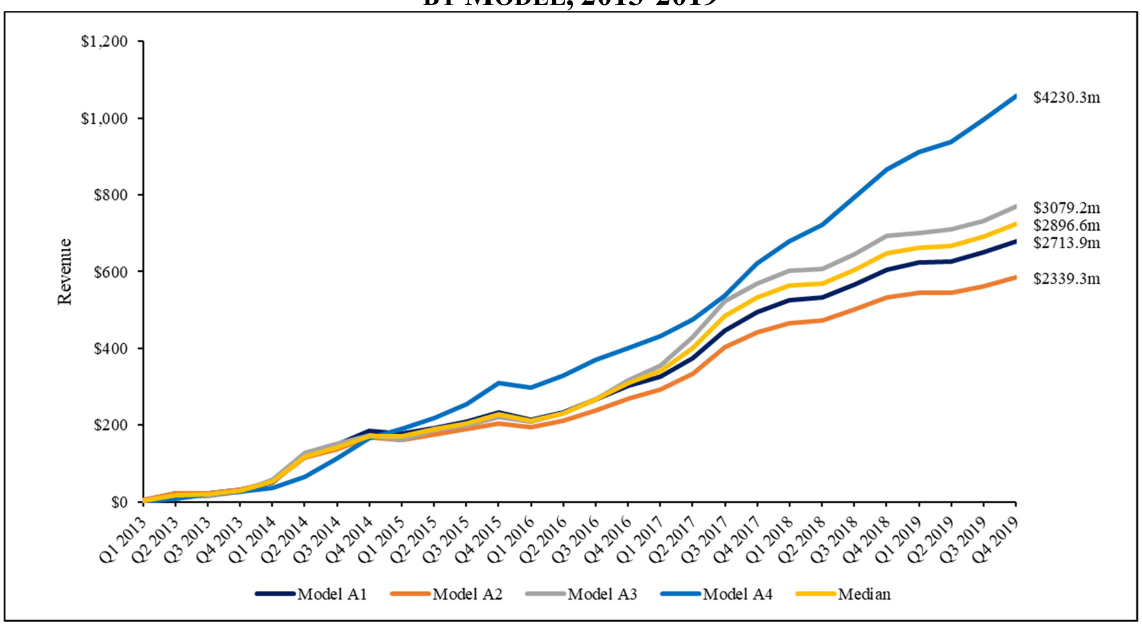
Specifically, the results for model A1 indicate that a one percent increase in the number of Instacart deliveries in an MSA increases grocery revenue by 0.004 percent. The results for model A2

[24] Paul A. Samuelson and William D. Nordhaus, *Economics*, 15th ed. (McGraw-Hill, 1995) at 209.

indicate that a one percent increase in Instacart GMV increases grocery revenue by 0.002 percent. The results for model A3 indicate that a one percent increase in the number of stores served by Instacart in an MSA increases grocery revenue by 0.009 percent. The results for model A4 indicate that a one percent increase in the number of quarters since Instacart's entry into an MSA is associated with 0.024 percent increase in grocery revenue. The results for model A5 indicate that Instacart entry is associated on average with a 2.1 percent increase in grocery revenue. For all five models, the coefficients on the Instacart adoption variables are statistically significant.

Figure 11 presents the increase in annualized grocery revenue attributable to Instacart based on the statistical estimates from Table 8 from Q1 2013 to Q4 2019. Again, each model indicates steady growth over time with the pace accelerating in 2017. By the end of 2013, the median estimate of the grocery revenue created by Instacart was $117.9 million; by the end of 2014, the median estimate of the grocery revenue created by Instacart was $681.7 million; by the end of 2015, the median estimate of the grocery revenue created by Instacart was $908.6 million; by the end of 2016, the median estimate of the grocery revenue created by Instacart was $1.2 billion; by the end of 2017, the median estimate of the grocery revenue created by Instacart was $2.1 billion; by the end of 2018, the median estimate of the grocery revenue created by Instacart was $2.6 billion; by the end of 2019, the median estimate of the grocery revenue created by Instacart was $2.9 billion as also indicated in Figure 1 in Section II.

**FIGURE 11:**
**GROCERY REVENUE ATTRIBUTABLE TO INSTACART**
**BY MODEL, 2013-2019**




## C. Average Wage Effects of Instacart Entry and Adoption

To date, there have been no statistical analyses assessing the impact of third-party grocery delivery services such as Instacart on the wages of grocery employees. However, some sources have posited that third-party grocery delivery may reduce grocery workers' wages by potentially changing the composition of jobs within the industry (see e.g., Carre and Tilly 2020). To test whether Instacart adoption is associated with lower grocery wages, the regressions from Table 5 are re-estimated using average monthly wage data for the grocery industry from QWI as the dependent variable. The regression estimates are presented in Table 9.[25] The results show that none of the coefficients on the Instacart adoption variables are statistically significant. Thus, there is no evidence that Instacart adoption causes grocery stores to substitute lower paying jobs for higher paying jobs.

**TABLE 9:**
**AVERAGE GROCERY WAGE**
**REGRESSION MODEL ESTIMATES**

| VARIABLES | A1 | A2 | A3 | A4 | A5 |
|---|---|---|---|---|---|
| log(Deliveries) | -0.000 | | | | |
| log(GMV) | | -0.000 | | | |
| log(Store Count) | | | 0.001 | | |
| log(Quarters Since Entry) | | | | 0.006 | |
| Instacart Presence | | | | | -0.000 |
| log(Non-Grocery Employment) | 0.116 | 0.116 | 0.109 | 0.104 | 0.115 |
| Personal Income per Capita | 0.003* | 0.003* | 0.003* | 0.003* | 0.003* |
| log(GDP) | -0.085 | -0.085 | -0.085 | -0.087 | -0.085 |
| log(Consumer Expenditures on Food and Beverage Goods) | -0.105 | -0.105 | -0.107 | -0.105 | -0.105 |
| log(Consumer Expenditures on Food Services) | 0.156 | 0.155 | 0.151 | 0.143 | 0.155 |
| Constant | 6.370* | 6.375* | 6.551* | 6.717* | 6.408* |
| Observations | 13,473 | 13,473 | 13,473 | 13,473 | 13,473 |
| R-squared | 0.470 | 0.470 | 0.470 | 0.470 | 0.470 |
| Number of MSAs | 424 | 424 | 424 | 424 | 424 |
| MSA Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Quarter Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Region-Year Fixed Effects | Yes | Yes | Yes | Yes | Yes |

*Sources: See Table 1 sources. [1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level. [4] All regressions have robust standard errors clustered by state. [4] Observations with average wages below the 0.1 percentile and above the 99.9 percentile are dropped from the regression sample.*

# V. Statistical Estimation of the Post-Pandemic Instacart Adoption Models

## A. Employment Effects of Instacart Adoption During the COVID-19 Pandemic

The statistical models estimated in this section quantify the relationship between retail grocery employment and Instacart adoption during the peak of the COVID-19 pandemic in Q2 2020. As explained in Section III, the dependent variables in each regression and the Instacart adoption variables are differenced relative to their pre-pandemic values in Q4 2019. Hence, the dependent variable for each model is the change in (log) grocery employment between Q2 2020 and Q4 2019. The independent variable of interest in model C1 is the change in (log) Instacart deliveries between Q2 2020 and Q4 2019. In model C2, the independent variable of interest is the change in (log) Instacart GMV between Q2 2020 and Q4 2019. Table 10 presents the results. The first two columns

[25] The models in Table 9 are estimated weighting by Q4 2019 grocery employment to provide estimates that are representative of wage impacts across employees. The results are similar if the models are estimated without weighting.

present the results of estimating models C1 and C2 without IV estimation, while the second columns present the results using the Quarters Since Entry variable as an instrument.

**TABLE 10:**
**COVID-19 EMPLOYMENT**
**REGRESSION MODEL ESTIMATES**

| VARIABLES | C1 | C2 | IV C1 | IV C2 |
|---|---|---|---|---|
| log(Deliveries) (Q4 2019-Q2 2020) | 0.010* | | | |
| log(GMV) (Q4 2019-Q2 2020) | | 0.007* | | |
| log(Deliveries) (Q4 2019-Q2 2020): IV | | | 0.022* | |
| log(GMV) (Q4 2019-Q2 2020): IV | | | | 0.020* |
| log(Non-Grocery Employment) (Q4 2019- Q2 2020) | 0.153 | 0.158 | 0.133 | 0.138 |
| Personal Income per Capita | 0.000 | 0.000 | 0.000 | 0.000 |
| log(GDP) | 0.004 | 0.005 | 0.002 | 0.002 |
| Population Density | -0.000 | -0.000* | -0.000 | -0.000 |
| COVID Cases per Capita Q2 2020 | 0.309 | 0.310 | 0.144 | 0.074 |
| COVID Deaths per Capita Q2 2020 | -0.802** | -0.800** | -0.798** | -0.790** |
| Constant | -0.026 | -0.029 | -0.012 | -0.010 |
| Observations | 840 | 840 | 840 | 840 |
| R-squared | 0.218 | 0.217 | 0.208 | 0.200 |
| State Fixed Effects | Yes | Yes | Yes | Yes |

*Sources: See Table 3 sources. [1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level. [4] All regressions have robust standard errors clustered by state.*

As indicated in the Table 10, each regression controls for the change in total county-level employment excluding grocery employment between Q2 2020 and Q4 2019, personal income per capita, real GDP, population density, the number of COVID-19 cases and deaths, and for the state in which the county is located.[26] Each regression includes 840 counties across the 50 U.S. states, and standard errors are clustered by state.

The coefficients on the Instacart adoption variables reflect a positive relationship between Instacart adoption and employment during the pandemic and are statistically significant regardless of which estimation strategy is used. As discussed above, the primary estimates presented in the third and fourth columns are derived using IV estimation to control for potential simultaneity in the relationship between grocery demand and Instacart adoption. The results indicate that simultaneity bias causes the regression results to understate rather than overstate the degree to which Instacart increases grocery employment. The results for model C1 estimated using IV indicate that a counterfactual one percent increase in Instacart deliveries in Q2 2020 relative to Q4 2019 increases grocery employment by 0.022 percent. The results for model C2 estimated using IV indicate that a counterfactual one percent increase in Instacart GMV in Q2 2020 relative to Q4 2019 increases grocery employment by 0.020 percent.

It is notable that the coefficient estimates in Table 10 are larger in magnitude than the pre-pandemic estimates based on the deliveries and GMV models (A1 and A2) in Table 5. This comparison

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[26] BEA variables including GDP, per capita personal income, and population are based on the most recent available estimates from 2019. These variables thus do not control for economic shocks associated with the outbreak of COVID-19. Population density is computed based on 2019 BEA population data and 2010 Census land area data.

indicates that the Instacart Effect became proportionally stronger during the pandemic as consumers opted for grocery delivery to avoid in-store shopping. Figure 6 in Section II calculates employment impacts during the pandemic based on the coefficient estimates in Table 10.[27]

As in the previous section, each model is again subjected to six placebo tests. For these placebo tests, each model is estimated by replacing the dependent variable, grocery employment, with employment in the book store, sporting goods and hobby store, general merchandise store, furniture store, and clothing store industries and the entire non-grocery retail sector. Table 11 displays the estimated coefficients on the Instacart adoption variables by model for each of the placebo industries.

**TABLE 11:**
**COVID-19 PLACEBO TEST RESULTS**
**BY INDUSTRY**

| Models | log(Book Store Employment) | log(Sporting Goods Store Employment) | log(General Merchandise Store Employment) | log(Furniture Store Employment) | log(Clothing Store Employment) | log(Non-Grocery Retail Employment) |
|---|---|---|---|---|---|---|
| IV C1 | 0.422 | -0.085 | -0.006 | -0.052 | -0.307 | -0.007 |
| IV C2 | 0.491 | -0.072 | -0.005 | -0.046 | -0.324 | -0.007 |

*Sources: See Table 3 sources. [1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level. [4] All regressions have robust standard errors clustered by state.*

As shown in Table 11, none of the Instacart adoption coefficients are statistically significant. These additional placebo tests provide further evidence that the regression results are driven by the specific relationship between Instacart adoption and economic growth in the grocery industry and not by economic shocks related to e-commerce or other factors affecting retail demand.

## B. Output Effects of Instacart Adoption During the COVID-19 Pandemic

As in the pre-pandemic entry and adoption analysis, in Table 12 the regressions from Table 10 are re-estimated using grocery payroll as a proxy for the change in grocery output measured in terms of revenue.

[27] For each MSA, the counterfactual level of Instacart deliveries and GMV had the COVID-19 pandemic not occurred is proxied using the values of these variables in Q4 2019.

**TABLE 12:**
**COVID-19 REVENUE**
**REGRESSION MODEL ESTIMATES**

| VARIABLES | C1 | C2 | IV C1 | IV C2 |
|---|---|---|---|---|
| log(Deliveries) (Q4 2019-Q2 2020) | 0.015** | | | |
| log(GMV) (Q4 2019-Q2 2020) | | 0.010** | | |
| log(Deliveries) (Q4 2019-Q2 2020): IV | | | 0.039*** | |
| log(GMV) (Q4 2019-Q2 2020): IV | | | | 0.036*** |
| log(Non-Grocery Employment) (Q4 2019- Q2 2020) | 0.061 | 0.070 | 0.021 | 0.030 |
| Personal Income per Capita | -0.000 | -0.000 | -0.000 | -0.000 |
| log(GDP) | -0.000 | 0.000 | -0.005* | -0.006* |
| Population Density | -0.000*** | -0.000*** | -0.000*** | -0.000*** |
| COVID Cases per Capita Q2 2020 | -1.033 | -1.019 | -1.360 | -1.486 |
| COVID Deaths per Capita Q2 2020 | -0.244 | -0.241 | -0.235 | -0.222 |
| Constant | 0.118*** | 0.112** | 0.109** | 0.113*** |
| Observations | 840 | 840 | 840 | 840 |
| R-squared | 0.294 | 0.291 | 0.264 | 0.239 |
| State Fixed Effects | Yes | Yes | Yes | Yes |

*Sources: See Table 3 sources. [1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level. [4] All regressions have robust standard errors clustered by state.*

Again, the coefficients on the Instacart adoption variables are statistically significant regardless of which estimation strategy is used and indicate that simultaneity bias causes the regression results to understate rather than overstate the degree to which Instacart increases grocery output. The results for model C1 estimated using IV indicate that a counterfactual one percent increase in Instacart deliveries in Q2 2020 relative to Q4 2019 increases grocery revenue by 0.039 percent. The results for model C2 estimated using IV indicate that a counterfactual one percent increase in Instacart GMV in Q2 2020 relative to Q4 2019 increases grocery revenue by 0.036 percent. The revenue impacts based on Table 12 are presented in Figure 6 in Section II.

## C. Average Wage Effects of Instacart Adoption During the COVID-19 Pandemic

Table 13 presents the results of re-estimating the post-pandemic regression models using average weekly wage from QCEW as the dependent variable.[28] As explained above, the dependent variables and primary independent variables of interest for the average wage analysis represent levels in Q2 2020 rather than differences relative to Q4 2019.

[28] As with the pre-pandemic average wage results, the models in Table 13 are estimated weighting by Q2 2021 grocery employment to provide coefficient estimates that are representative of average wage impacts across employees. The results are again similar if the models are estimated without weighting.

**TABLE 13:**
**COVID-19 AVERAGE WEEKLY WAGE**
**REGRESSION MODEL ESTIMATES**

| VARIABLES | C1 | C2 | IV C1 | IV C2 |
|---|---|---|---|---|
| log(Deliveries) (Q2 2020) | 0.024*** | | | |
| log(GMV) (Q2 2020) | | 0.017*** | | |
| log(Deliveries) (Q2 2020): IV | | | 0.037*** | |
| log(GMV) (Q2 2020): IV | | | | 0.024*** |
| log(Non-Grocery Employment) (Q2 2020) | -0.032 | -0.029 | -0.058*** | -0.048** |
| Personal Income per Capita | 0.002*** | 0.002*** | 0.002*** | 0.002*** |
| log(GDP) | 0.023 | 0.026 | 0.032 | 0.035 |
| Population Density | -0.000*** | -0.000*** | -0.000*** | -0.000*** |
| COVID Cases per Capita Q2 2020 | 4.638** | 4.433** | 5.087*** | 4.705*** |
| COVID Deaths per Capita Q2 2020 | 0.268 | 0.295 | 0.197 | 0.250 |
| Constant | 5.897*** | 5.800*** | 5.852*** | 5.708*** |
| Observations | 868 | 868 | 868 | 868 |
| R-squared | 0.766 | 0.768 | 0.761 | 0.764 |
| State Fixed Effects | Yes | Yes | Yes | Yes |

*Sources: See Table 3 sources. [1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level. [4] All regressions have robust standard errors clustered by state.*

Again, the coefficients on the Instacart adoption variables are statistically significant regardless of which estimation strategy is used and indicate that simultaneity bias causes the regression results to understate rather than overstate the degree to which Instacart increases the average grocery wage. The results for model C1 estimated using IV indicate that a one percent increase in Instacart deliveries increases the average grocery wage by 0.037 percent. The results for model C2 estimated using IV indicate that a one percent increase in Instacart GMV increases the average grocery wage by 0.024 percent.

Figure 8 in Section II uses the coefficient estimates from Table 13 to estimate the average increase in grocery wages attributable to Instacart in Q2 2020 in markets served by Instacart. As shown in Figure 8, the increase in the average wage of grocery workers attributable to Instacart during the COVID-19 pandemic ranges from $19.59 to $25.16 with a median estimate of $22.37. The employment-weighted average weekly wage for counties with Instacart sales in the regression sample is $569. Thus, the results show that without the increase in Instacart usage during the pandemic, grocery wages would have been 3.4 to 4.4 percent lower in markets served by Instacart.

The increase in average grocery wages attributable to Instacart demonstrates that Instacart not only benefits grocery workers by creating jobs, but also has the potential to increase wages depending on economic conditions. That is, the evidence indicates that Instacart adoption during the pandemic enabled grocery workers to enjoy higher wages in a similar manner to the way in which demand-based pricing enables workers in the app-based economy to earn more when demand is high. The evidence that Instacart increased grocery workers' wages during the COVID-19 pandemic also further belies the hypothesis that third-party grocery delivery threatens to cause grocery stores to substitute lower paying jobs for higher paying jobs. The statistical analyses uniformly indicate a symbiotic relationship between Instacart and the U.S. grocery industry and its workers.

# VI. Conclusion

This study provides strong evidence of a causal connection between Instacart adoption and economic growth in the grocery industry before and during the COVID-19 pandemic. The results demonstrate that the Instacart Effect, i.e. the causal relationship between economic outcomes in the grocery industry and Instacart adoption documented in Kulick (2020), is a national phenomenon creating significant gains in grocery employment and revenue throughout the United States. Furthermore, there is no evidence that Instacart adoption has changed the composition of jobs within the grocery industry resulting in lower average wages for grocery workers. Indeed, during the COVID-19 pandemic, Instacart adoption increased grocery workers' wages by enabling the industry to meet surging demand. Instacart adoption has thus driven increased grocery sales while expanding employment and increasing wages in the industry at a time when other retail industries and their workers are facing disruption and displacement due to the rise of e-commerce and the impact of the COVID-19 pandemic.

# Appendix 1

This appendix presents the results of estimating the pre-pandemic employment regression models A1-A4 and the post-pandemic employment regression models C1-C2 using root functions rather than the log of each Instacart adoption variable. Like the log function, root functions are concave and thus imply diminishing returns to Instacart adoption. Unlike the log function, root functions permit zero-valued observations and thus can be used to estimate the models including observations with no Instacart presence without adding one to the value of the Instacart adoption variables. Because the log function is more commonly used in economic research, has a convenient interpretation in terms of percentage effects, and does not require selection of a specific root function from a family of distinct functional forms, the primary results are reported using the log function and transforming the variables by adding one. However, Tables 1-1 and 1-2 demonstrate that the statistical results are not driven by the transformation of the underlying variables and are robust to alternative functional forms. Table 1-1 presents the results for the pre-pandemic models A1-A4.

**TABLE 1-1:**
**GROCERY EMPLOYMENT REGRESSION MODEL ESTIMATES USING ALTERNATIVE SPECIFICATIONS OF THE INSTACART ADOPTION VARIABLES**

| Models | Natural Log | 3rd Root | 4th Root | 5th Root | 6th Root | 7th Root | 8th Root | 9th Root | 10th Root |
|---|---|---|---|---|---|---|---|---|---|
| A1 | 0.004*** | 0.001*** | 0.003*** | 0.006*** | 0.009*** | 0.011*** | 0.013*** | 0.014*** | 0.015*** |
| A2 | 0.003*** | 0.000*** | 0.001*** | 0.002*** | 0.004*** | 0.006*** | 0.007*** | 0.009*** | 0.010*** |
| A3 | 0.011*** | 0.010*** | 0.015*** | 0.019*** | 0.021*** | 0.022*** | 0.023*** | 0.024*** | 0.024*** |
| A4 | 0.026*** | 0.026*** | 0.028*** | 0.029*** | 0.029*** | 0.029*** | 0.029*** | 0.029*** | 0.029*** |

No root function precisely matches the shape of the log function, and thus a range of root functions are considered in implementing this robustness test. The square-root function displays significantly less concavity than the log function over the relevant range of values of the Instacart adoption variables. Thus, Table 1-1 compares the Instacart adoption coefficients estimated using the log function to the results estimated using the 3$^{rd}$ through 10$^{th}$ roots of each adoption variable. As indicated in Table 1-1, all coefficients are positive and statistically significant demonstrating that the results for the pre-pandemic models are highly robust. Table 1-2 presents the results for the post-pandemic models C1-C2.

**TABLE 1-2:**
**COVID-19 EMPLOYMENT REGRESSION MODEL ESTIMATES USING ALTERNATIVE SPECIFICATIONS OF THE INSTACART ADOPTION VARIABLES**

| Models | Natural Log | 3rd Root | 4th Root | 5th Root | 6th Root | 7th Root | 8th Root | 9th Root | 10th Root |
|---|---|---|---|---|---|---|---|---|---|
| IV C1 | 0.022* | 0.010* | 0.019** | 0.031** | 0.045** | 0.060** | 0.076** | 0.092** | 0.109** |
| IV C2 | 0.020* | 0.002* | 0.006** | 0.012** | 0.020** | 0.029** | 0.040** | 0.051** | 0.064** |

Again, all coefficients are positive and statistically significant demonstrating that the results for the post-pandemic models are also highly robust.

NERA
ECONOMIC CONSULTING

NERA Economic Consulting
1255 23rd Street NW
Washington D.C. 20037
Tel: 1 (202) 466-3510  Fax: 1 (202) 466-3605
www.nera.com