Inflation with Covid Consumption Baskets

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Abstract

The Covid-19 Pandemic led to changes in expenditure patterns that introduced significant bias in the measurement of Consumer Price Index (CPI) inflation. Using publicly-available data on card transactions, I updated the official CPI weights and re-calculated inflation with Covid consumption baskets during 2020. I show that the US CPI *underestimated* the Covid inflation rate, as consumers spent relatively more on food with positive inflation, and less on transportation and categories experiencing deflation. The bias peaked in May, when US Covid annual inflation was 1.02% compared to just 0.13% in the CPI and low-income households were experiencing nearly twice as much inflation as those at the top of the income distribution. I find similar evidence of higher Covid inflation in 14 of 19 additional countries.

JEL-Codes: C43,E21,E31.
Keywords: COVID, consumer expenditures, CPI, inflation.

1 Introduction

The Covid-19 Pandemic led to lockdowns, mobility restrictions, and health concerns that dramatically changed consumer expenditure patterns in many countries during 2020, as documented by Chetty et al. (2020) and Carvalho et al. (2020).[1] In particular, consumers drastically reduced their spending on transportation, hotels, restaurants, and recreation, while expenditures on food and other groceries increased in both absolute and relative terms.

These sudden changes in expenditure patterns can introduce significant biases in the Consumer Price Indices (CPIs) used to measure inflation, as noted theoretically by Diewert and Fox (2020) and Soloveichik (2020). The reason is that most National Statistical Offices (NSOs) only update the CPI basket weights once a year with lagged expenditure data. The US Bureau of Labor Statistics (BLS), for example, updated the weights in December 2019 using expenditure information collected back in 2017-2018.[2] While this practice may be reasonable in normal times,[3] it can obscure changes in inflation dynamics and inequality after a large shock such as the Covid Pandemic.

In this paper, I quantify the impact that changes in Covid expenditure patterns had on the measurement of CPI inflation during 2020. Relying on publicly-available data from credit and debit card transactions, I update official CPI weights and build alternative "Covid Basket" price indices in 20 countries from March to December 2020.

I start with the US, where daily Covid expenditures were published by the Opportunity Insights (OI) Economic Tracker at Harvard and Brown University, described in Chetty et al. (2020). I find that US Covid inflation was significantly higher for the all-items CPI for the first three months of the Pandemic, as social-distancing rules and preferences induced more consumer expenditure in food and groceries (where prices were increasing) and prevented spending in categories such as transportation (where there was significant deflation). By May, the annual inflation rate of the US Covid index was 1.02%, compared to only 0.13% of the official CPI (all-items, US city average, not seasonally adjusted). The difference narrowed in the following

[1] See also Baker et al. (2020), Andersen et al. (2020), Dunn et al. (2020), and Coibion et al. (2020).

[2] In May 2022 the US BLS announced a shift to updating the CPI weights annually with expenditure data from a single previous calendar year. These changes were promising, but the updates are not frequent enough to reduce the biases identified in this paper.

[3] For example, the fixed-basket weights can mitigate problems such as chain-drift present in some chained price indices.

months, but by December the US Covid index still had an annual rate of 1.80%, compared to 1.38% in the fixed-basket CPI. Furthermore, I find a similar bias in the Core CPI, after excluding food and energy.

Next, I use the BLS consumer expenditure (CEX) survey to build income-specific CPI weights and show that Covid inflation was higher for low-income households, who traditionally spend relatively more on food and less on transportation. The difference between the bottom and top quintiles of the income distribution peaked in May, when the low-income inflation rate was 1.34% compared to just 0.47% for high-income households. By December, low-income households were still experiencing 0.33% more annual inflation. This gap was driven by the initial differences in basket weights across income groups, rather than by the relative changes experienced during the Pandemic, suggesting that even small discrepancies in upper-level expenditures can have a significant impact on inflation inequality during events like Covid, when there are sudden changes in relative inflation rates at the sector level.

Finally, I provide estimates of the Covid CPI rates in 19 other countries. Due to data limitations, in most cases I update the official CPI weights with the US Covid expenditure patterns, with the exception of nine European countries where I use credit and debit card spending estimates from Spain computed by Carvalho et al. (2020). Consistent with the US results, in 14 countries I find that the Covid-basket inflation rate was higher than that of the official CPIs in December 2020. The magnitude of the difference varies greatly by country, and is largest in places experiencing more food inflation, such as Brazil.

These results have important implications for policy-makers trying to respond to the crisis. First, they suggest that the cost of living was higher than estimated by the official data at the time, with welfare effects that are particularly relevant for low-income households. Second, they can help explain why consumer inflation expectations increased in many countries, consistent with the recent literature that shows that consumers use their purchasing experiences to form expectations about the future.[4] Third, they reinforce the fact that, despite the collapse in output, there was little disinflation during the first few months of the Covid crisis. This is consistent with the view that the Pandemic combines a negative demand shock with supply disruptions that were putting upward pressure on prices in many sectors.

[4]See Coibion and Gorodnichenko (2015), Cavallo et al. (2017), and D'Acunto et al. (2019)

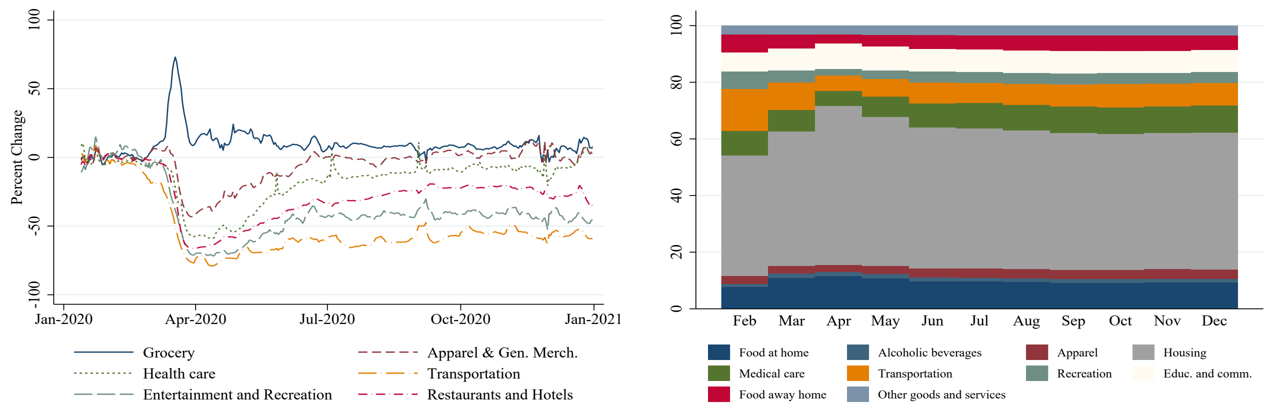
More generally, my findings show that the increasing availability of high-frequency expenditure data provides a simple and effective way to build price indices that can adjust for sudden changes in consumption baskets, significantly improving the accuracy of inflation statistics during times of crisis.[5]

2 Data and Methodology

To build the "Covid weights," I start with daily measures of the change in US consumption across sectors since January 2020, available at the Opportunity Insights (OI) Tracker[6]. They are constructed using anonymized and aggregated transactional data collected from credit and debit card transactions in the US, as described by Chetty et al. (2020). The data are processed through several steps to ensure accuracy and reliability, including adjusting for sharp changes in the client base, addressing spurious changes and outliers, controlling for seasonal fluctuations, and making comparisons and adjustments with national benchmarks obtained from official survey-based statistics.[7]

These measures, plotted in Figure 1(a), show that consumer spending quickly dropped by up to 70% in most categories by the end of March. Over time, expenditures in "Apparel", "General Merchandise", and "Health Care" slowly recovered, but spending in "Transportation" and "Entertainment and Recreation" were still about 50% below pre-pandemic levels by September. The only category where spending increased was "Groceries", peaking in late March and remaining about 10% above pre-pandemic levels in the following months.

[5]All the data, code, and updated results from this paper are available at projects.iq.harvard.edu/covid-cpi.
[6]See tracktherecovery.org
[7]See Chetty et al. (2020) for more details



(a) Consumer Spending (Opportunity Insights)

(b) Covid Basket Weights

Figure 1: Consumer Spending and CPI Basket Weights in 2020

Notes: Figure (a) shows the expenditure change across categories of goods and services in the US since January 2020. These estimates are computed by Chetty et al. (2020) using data collected from credit and debit card transactions. The data is publicly available at the Opportunity Insights (OI) "Track the Recovery" website (tracktherecovery.org). Figure (b) shows the Covid basket weights estimated by combining the data in (a) with the official CPI weights from the Bureau of Labor Statistics.

I combine these estimates with official CPI data from January 2019 to December 2020, obtained from the official NSO in each country, including the Bureau of Labor Statistics in the US. In all cases, I use the upper-level sector series that compose the headline CPI (all-items, not-seasonally adjusted), as well as the latest available expenditure weights for each of these sectors in the official CPI.

The matching of the OI categories with the CPI sectors requires some assumptions. To improve the correspondence, I split the US CPI for "Food and Beverages" into three additional subcategories. About six categories are then matched across datasets. For "Food at Home" and "Alcoholic Beverages," I use the OI "Grocery" category. For "Food Away from Home," I use the OI category for "Restaurants and Hotels." For "Other Goods and Services," I assume that the expenditure changes are equal to those of the whole OI basket. Finally, for "Housing" and "Education and Communication," I assume that expenditures in these categories have not changed, which seems a reasonable assumption during the first months of the Pandemic. More details on this matching are provided in the Appendix.

To estimate the expenditure shares in the Covid basket, I start with the latest official CPI weights and multiply them by the average percentage change in the corresponding expenditure category each month.[8] The new weights are then re-computed as a share of the total, to account for the fact that total expenditure is also falling over time.

Formally, the Covid weights are given by:

$$s_t^i = \frac{P_t^i Q_t^i}{\sum_i P_t^i Q_t^i} = \frac{s_0^i \Delta e^i}{\sum_i s_0^i \Delta e^i} \tag{1}$$

where P_t^i and Q_t^i are the prices and quantities of CPI category i at time t, and $\Delta e^i = \frac{P_t^i Q_t^i}{P_0^i Q_0^i}$ is the change in expenditure. Equation 1 highlights the fact that these are *relative* weights, so the importance of a category in the basket can change even when its expenditure is not affected.

Finally, the CPI and Covid price indices are computed using the weighted sum of the changes in the official CPI sectoral indices, using weights s_0^i and s_t^i, respectively. Note the fixed-basket CPI is Laspeyres index, which traditionally results in *higher* inflation because it does not allow for the possibility that consumers shift their spending away from categories experiencing relatively more inflation. By using more current expenditure weights in the Covid Index, I am allowing for this possibility, which makes my results with the Covid basket more surprising.[9]

2.1 Data Limitations

The OI consumer spending data, while insightful, does have many limitations and may not fully represent total consumer spending in the United States.

Firstly, it's crucial to note that card transactions are prevalent in sectors like retail and food services, but sectors like housing and education, where payments are often not made via cards, are not represented. This requires me to make assumptions about the uncovered sectors. As previously stated, I assume that expenditures in housing and education remained unchanged from March to December 2020 —a reasonable assumption during the early months of the pandemic. However, for a more prolonged analysis, it would be necessary to supplement card data with other data sources for these sectors.

[8] Most NSOs compute a Lowe Index formula at upper levels of aggregation. This introduces small adjustments to the weight to account for relative price changes across categories every month, but they have little impact on the basket weights because quantities are assumed to be fixed. These small price adjustments produce a set of new weights called "relative importance ratios". In this paper, the term "official CPI weights" is used to refer to these relative importance ratios. See the BLS website for more details.

[9] The Covid index is not a Paasche index because I am not fixing the basket weights to the last period. Instead, my method is closer to the "Chained CPI" produced by the BLS (C-CPI-U). Unfortunately, the BLS can only update expenditure weights gradually, which results in a preliminary C-CPI-U index that does not fully reflect spending patterns until a year later, when a final version is published. In fact, in the Appendix I show that the C-CPI-U has had less inflation during the Pandemic than the CPI-U, the benchmark all-items CPI used in this paper.

Secondly, the data may not be representative of spending patterns with other payment methods, such as cash transactions. Chetty et al. (2020) acknowledge this limitation and attempt to address it by comparing card spending data with cash purchase data from another company. They find that the trends in card and cash spending are similar, suggesting that households shifted spending similarly across both modes of payment during the Pandemic. However, this comparison is limited to grocery spending, and the trends in other categories remain less clear.

Thirdly, the data may not accurately represent the entire US population. It could be biased towards the clientele of the data provider or some sectors or geographies where card payments are more common. Chetty et al. (2020) address many of these issues and provide some reassurances. For example, the spending series are well aligned with the Advance Monthly Retail Trade Survey used to construct official national accounts. They conclude that the data is representative of total card spending in the US, but not necessarily total spending.

A significant concern for my study is that people with varying incomes may utilize their cards differently in response to large shocks. This could potentially affect the reliability of the observed changes in spending patterns across different income levels, and consequently, introduce bias into the inflation inequality findings in Section 3.3. However, the disparities found in that section are not primarily driven by differences in spending patterns during the Covid period, but rather by variations in the initial weights computed from official survey data.

Finally, this type of data may be more susceptible to sampling errors than survey-based estimates. The magnitude of the COVID shock in my paper is substantial enough to render this a minor concern. However, for smaller economic shocks, changes in spending patterns may not be easily distinguishable from sampling noise.

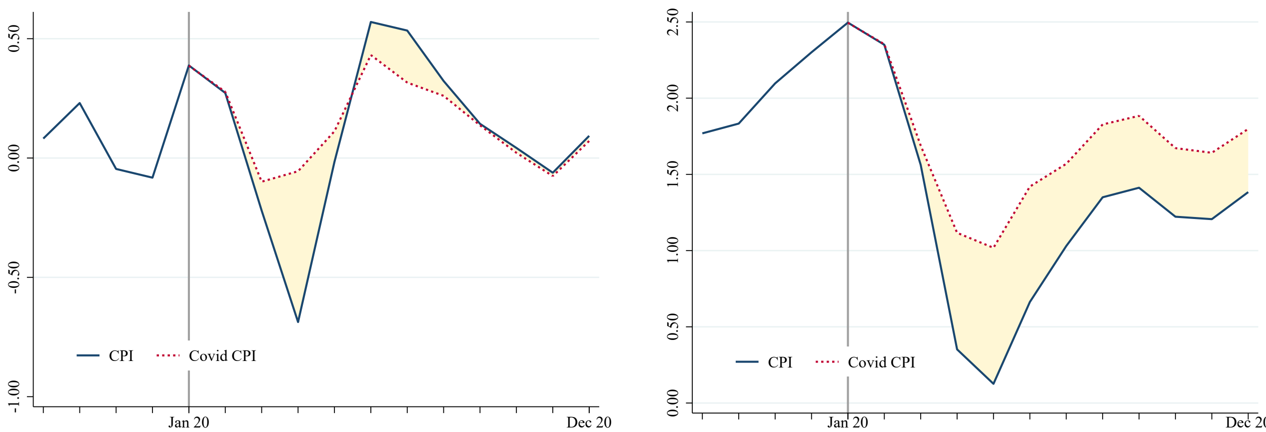
Overall, these limitations suggest that this card data should be used as a complement to traditional expenditure measures. It can be particularly useful to build alternative price indices for high-frequency analysis during times of large shocks and crises, but not to replace survey-based expenditure data sources in the construction of CPI weights.

3 Impact on US Inflation

In this section, I look at the impact in the US for the all-items CPI, extend the analysis to the Core CPI, and discuss potential welfare implications by comparing Covid inflation for both low and high-income households.

3.1 All-items CPI

The all-items CPI for urban consumers (CPI-U) is the main "headline" measure of inflation in the US. Figure 2(a) shows the impact that the changes in expenditure shares across categories have on this index for every month since the Pandemic started.



(a) Monthly Inflation Rate (%)

(b) Annual Inflation Rate (%)

Figure 2: US Inflation During the Covid Pandemic

Notes: These graphs show the all-items, US city average, not seasonally adjusted CPI, and an equivalent index constructed using estimates of the consumption expenditure shares under lockdown.

During the first three months of the Pandemic, from March to May, the Covid CPI experienced significantly less deflation. In March, when the Pandemic first hit the US, the Covid index had only half the deflation shown by the fixed-basket CPI. In April, the difference became even larger, with the Covid CPI falling by only -0.09% compared to a fall of -0.69% in the CPI. Interestingly, that month the trend in the Covid CPI was already rebounding. In May, the Covid CPI has a positive inflation rate, while the CPI was still experiencing some deflation.

The following three months, from June to August, the direction of the CPI bias was reversed, and inflation started being *lower* with the Covid basket. In particular, in June and July, the fixed-basket CPI was assigning too much weight to the transportation sector, where prices were now rebounding, even though expenditure levels remained significantly below pre-pandemic levels.

Although the sign and magnitude of the bias changed over time, the annual inflation rate for the Covid index has been consistently higher than that of the fixed-basket CPI, as shown in

Figure 2(b). The difference was largest in May, when Covid inflation was 0.95% compared to just 0.13% in the CPI. By September, the Covid index was still experiencing an annual inflation rate equal to 0.95% compared to only 0.13% in the official CPI.

To understand why the Covid index has more inflation, consider the CPI sectors and weights shown in Table 1 for April 2020, when the difference was largest. The first column shows a comprehensive list of all the CPI categories that compose the all-items index. The second column shows the monthly CPI sector inflation for that month. The third and fourth columns show the CPI and Covid weights. Finally, the last two columns show the incidence that each category has on the total inflation rate. The incidence is the monthly inflation rate multiplied by the weight, so that the sum of all the numbers in the last two columns equals the -0.69% and -0.09% monthly inflation rates for CPI and Covid CPI during April.

	Monthly	Weight		Incidence	
CPI Category	CPI Inflation	CPI	Covid CPI	CPI	Covid CPI
Food at Home	2.67	7.58	11.28	0.20	0.30
Alcoholic Beverages	0.30	1.02	1.52	0.00	0.00
Apparel	-4.38	2.81	2.20	-0.12	-0.10
Housing	-0.03	42.11	55.80	-0.01	-0.02
Medical Care	0.28	8.83	5.60	0.02	0.02
Transportation	-4.97	15.74	6.25	-0.78	-0.31
Recreation	-0.27	5.82	2.23	-0.02	-0.01
Education and Communication	0.13	6.77	8.97	0.01	0.01
Food Away from Home	0.15	6.19	3.13	0.01	0.00
Other Goods and Services	-0.04	3.13	3.03	0.00	0.00

Table 1: US CPI Weights and Incidence - April 2020

Notes: The CPI weight is the share of expenditure in a given category over total expenditures. Note that categories that experience no change in spending over time can have higher Covid weights as a share of the decreasing total expenditure basket. The incidence is the monthly inflation rate multiplied by the weight. The sum of all the category incidence numbers is equal to the monthly inflation rate.

Table 1 shows that the US Covid inflation rate was higher in April mainly because there was more weight in categories that had a positive inflation rate, and less weight in categories experiencing significant deflation. In particular, the weight for "Food at Home" rose from 7.58% to 11.28%, increasing the incidence of this category by 0.10%. At the same time, the weight for "Transportation" fell from 15.74% to 6.25%, increasing the incidence on the total monthly inflation rate by about 0.47%. The weights of "Housing" and "Education and Communication" also rose significantly. However, these two categories had little impact on Covid inflation because their sectoral inflation rates are close to zero.

3.2 Core CPI and PCE Index

Although much of the basket bias comes from the changes in spending on food and fuel, there is also higher Covid inflation in the Core CPI index that excludes these categories, as shown in Figure A2 in the Online Appendix.[10] The difference was largest in the first three months of the Pandemic, and by September the annual inflation rate for the Covid basket Core index was 1.98% compared to the 1.74% in the BLS Core.

The reason for the higher Core inflation is that the Covid basket puts less weight on non-energy transportation categories that were having significant deflation in April and May, such as "Public Transportation" and "New and Used Motor Vehicles." Although the magnitude of the bias is smaller with the Core, its effects may be more persistent because expenditures in transportation are taking longer to recover, as shown by the consumption patterns in Figure 1(a).

An alternative Core index in the US is the Personal Consumption Expenditures (PCE) deflator, used by the Federal Reserve for its official inflation target. There are many methodological differences with the CPI, but a key distinction is that the PCE is a chained index that tries to more frequently account for changes in expenditures using the Census Retail Trade Survey. Unfortunately, many sectors can only be adjusted on a quarterly basis, introducing delays.[11] Indeed, a comparison between the CPI and PCE Core indices shows that there was almost identical deflation in the Core CPI and PCE indices in March and April, suggesting that the PCE Core also underestimated the level of Covid inflation during that time.[12].

3.3 Impact by Income Level

My findings imply that the cost of living for consumers is rising faster during the Covid crisis than what the official CPI suggests. This can, in turn, have different welfare implications across income groups, depending on how much households spent during the crisis in categories such as food and transportation.

[10] To build the Core indices, I exclude all food series and split the "Housing" and "Transportation" series to remove their energy components. I also made similar assumptions for the consumer spending patterns at the category level, with details provided in the Appendix.

[11] See Bureau of Economic Analysis (2014).

[12] See Figure A3 in the Online Appendix

A large literature has studied how inflation varies across income levels. Earlier papers such as Hobijn and Lagakos (2005) compared expenditures at upper levels of aggregation and found small differences in inflation rates across income groups. In more recent years, Kaplan and Schulhofer-Wohl (2017), Argente and Lee (2017), and Jaravel (2019) used scanner data to study mechanisms that can increase the inflation experienced by low-income households within narrower categories of goods. For example, Jaravel (2019) found that annual inflation in the US for households in the bottom income quintile was on average nearly 0.4% higher for the period 2004-2015. For the Covid Crisis, Jaravel and O'Connell (2020) used UK scanner data to show that inflation increased for most households, but they found only modest differences in inflation rates across socio-demographic groups.

To study the impact for different households in the US, I construct expenditure weights for the lowest and highest quintiles of the household income distribution. These weights are not published by the BLS, so I estimate them with data from the 2018 BLS Consumer Expenditure Survey (CEX). The initial weights, shown in Table A5 in the Appendix, reflect that low-income households spend relatively more on "Food and Beverages", "Housing", "Medical Care", and "Other goods and Services", and relatively less in "Transportation" and other categories. I update these weights during Covid using monthly spending patterns provided by Opportunity Insights for the same income quintiles, and re-estimate the inflation rate experienced by each group during the crisis.[13]

Figure 3 shows the annual inflation rate for each income-level Covid index, as well as the benchmark official and Covid CPIs. During 2019, low-income households were already experiencing more inflation due to the fact that they spend relatively more on food. After March 2020, the Pandemic increased the difference. With Covid weights, the low-income households had an annual inflation rate of 1.12% in May 2020, compared to just 0.57% for high income households. The difference narrowed in the months that followed, but by September the Covid inflation rate for low-income households was still higher, at 1.99% compared to 1.73% for high-income families.

[13] More quintiles and other details on these weights and their construction are provided in the Appendix.

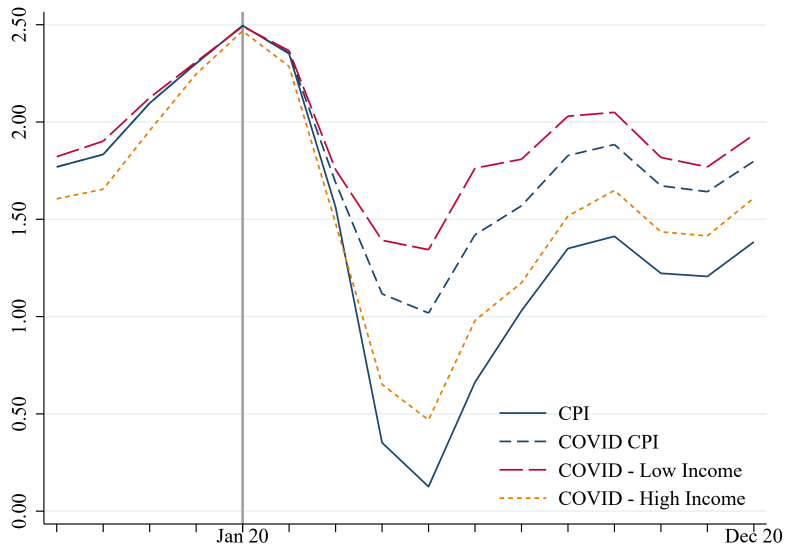


Figure 3: US Annual Inflation with Covid Expenditure Baskets

Notes: The CPI and Covid CPI are plots of the same indices shown in Table 1. The Covid Low (High) Income index uses CEX expenditure weights for households in the lowest (highest) quintile of the income distribution. These weights remain constant for 2019, and after January 2020, are updated using the changes in spending patterns for equivalent quintiles computed by Opportunity Insights. See the Appendix for details.

The changes in consumption patterns during Covid increased the inflation rate for both income groups, consistent with the UK results in Jaravel and O'Connell (2020). But the fact that low-income households spend relatively more on food, and less on transportation, made the Covid inflationary impact greater for those at the bottom of the income distribution. This was mainly driven by the initial differences in basket weights across income groups, rather than by the specific changes experienced during the Pandemic.[14] This suggests that even small differences in upper-level expenditure weights can have an impact on inflation inequality during events such as Covid.[15]

4 Impact in other Countries

In this section, I extend my analysis to 19 additional countries: Argentina, Brazil, Canada, Chile, Colombia, France, Germany, Greece, Ireland, Italy, Japan, Korea, Netherlands, Russia, South

[14] In fact, the increase in inflation of the Covid-basket index relative to a fixed-basket index is *smaller* for low-income households, because their changes in spending patterns have been less persistent over time (as documented by Chetty et al. (2020). In other words, inflation inequality is greater during Covid, but it is actually smaller than what would be measured with a fixed-basket index. See the Appendix for details.

[15] By contrast, differences in expenditure patterns at lower levels of aggregation may matter more in the long-run, as documented in Jaravel (2019).

Africa, Spain, Turkey, UK, and Uruguay. All these countries use the COICOP classification system, which is different from the one applied by the BLS in the US, but the category matching process and assumptions are very similar, as shown in the Appendix.

There is still no publicly-available Covid expenditure data in all these countries, so in most cases I simply assume that the Pandemic caused a similar change in consumption patterns as seen in the US data. This is clearly a rough approximation because spending patterns could be influenced by differences in infection rates, lockdown intensity, and the overall timing of the crisis. However, for a set of nine European countries where the timing of the Covid crisis was particularly different from the rest of the world, I use expenditure estimates from Spain computed by Carvalho et al. (2020).[16] Furthermore, there are many similarities in the Covid spending patterns from both data sources, particularly with the increase in spending for food at home and the collapse of expenditures for transportation, which matter the most for the inflation results presented below.[17]

Table 2 shows the CPI and Covid annual inflation rates for all countries in December 2020. Detailed weights and inflation dynamics in each country are shown in the Appendix.

[16] These data are published at https://www.bbvaresearch.com/en/special-section/charts/

[17] See the Appendix for a comparison of Covid spending patterns in the US and Spain.

Country	Annual Inflation (12-month change, %) CPI	Covid CPI	Difference
Brazil	4.81	5.88	1.07
Chile	2.96	3.55	0.59
Uruguay	9.52	10.08	0.56
South Africa	3.12	3.65	0.54
France	0.10	0.64	0.54
Korea	0.62	1.04	0.42
US	1.38	1.80	0.41
Spain	-0.06	0.34	0.39
Russia	4.93	5.21	0.28
Canada	0.65	0.83	0.19
Greece	-1.55	-1.38	0.17
Colombia	1.65	1.78	0.13
Japan	-0.93	-0.82	0.12
Italy	0.70	0.70	0.00
UK	0.68	0.52	-0.17
Ireland	-1.12	-1.45	-0.34
Netherlands	1.05	0.61	-0.44
Argentina	36.97	36.49	-0.48
Germany	-0.57	-1.05	-0.48
Turkey	14.09	13.41	-0.68

Table 2: CPI and Covid Inflation in December 2020

Notes: The top panel shows countries where the Covid inflation is higher than the fixed-basket CPI. The bottom panel shows countries where the Covid inflation is lower than the fixed-basket CPI. Covid inflation rates are constructed using official CPI weights in each country updated by the relative changes across categories observed in US data. Details on the incidence of CPI categories on the monthly inflation rate in each country are shown in the Appendix.

In the top panel, I list the countries where the Covid Inflation rate is higher than that of the official CPI, ranked by the percentage point difference. Consistent with the US results, in these 14 countries the higher Covid inflation rate is driven by an increase in expenditure weights for “Food and Beverages,” which was having more inflation, and a decrease in the weight of “Transportation,” which was having significant deflation. Brazil is at the top because the divergence in these two sectoral inflation rates was larger and more persistent over time.

The bottom panel shows that some countries appear to have *less* inflation with the Covid basket. In these cases, there is no common explanation across countries. For example, in Germany the Covid index has less weight on “Recreation and Culture,” a category with a surprisingly high inflation rate of 4.23% during April. In the Netherlands, instead, there was less Covid inflation because of a 7% spike in ”Restaurants and hotels” that same month. Understanding the specific inflation dynamics within each of these countries is outside the scope of this paper, but these results highlight the fact that the Covid basket bias described in this paper depends not only of the changes in the basket weights but also on the sectoral inflation rates experienced by each country.

My results outside the US are only approximations to the true Covid inflation rates in these countries, but they still suggest where there might be larger biases in measured CPI inflation. Reinsdorf (2020) applies a similar methodology and weights in 83 countries and finds that underestimation of inflation during the early months of the pandemic occurs in nearly all regions of the world. Recognizing the importance of these potential distortions, some NSOs such as the UK's ONS and Statistics Canada started to produce experimental indices with Covid adjustments by mid-2020, as discussed in ONS (2020) and Mitchell et al. (2020).[18] Future research papers could help expand these efforts by computing higher-frequency expenditure weights from transactional data collected in other countries.

5 Discussion and Other Potential Biases

As noted in Section 2, my findings go in the opposite direction of the *upward* CPI substitution bias that is well-documented in the literature. The usual claim is that the fixed-basket CPI does not take into account how consumers shift spending away from categories with relatively higher inflation and into categories experiencing more deflation. With the updated Covid weights, I am explicitly allowing for this to happen, so why do I find even higher inflation? In other words, why is this expenditure switching not happening during Covid?

The answer may lie within the characteristics of the Covid shock itself. One possibility is that the sectoral inflation differences during Covid are mostly driven by relative demand shocks (people consuming more groceries and less transportation because they have to stay home), whereas in normal times they might be driven by relative supply shocks (with a move *along* the demand curve in response to the change in prices). Large demand shocks were clearly important in this crisis, but there is also evidence that supply disruptions have played a significant role in some sectors.[19] Another possibility is that Covid made demand more inelastic in some sectors. Indeed, it is reasonable to expect consumers to be less responsive to price changes in times of

[18] See also Dixon (2020)

[19] See Cavallo and Kryvtsov (2020).

lockdowns and social-distancing, when they are forced to consume food at home even if prices rise, or are unable or unwilling to travel even if fuel prices collapse. In fact, these two explanations are not mutually exclusive, and are both likely playing a role during Covid.

A third possibility is that consumers could be making the expenditure switching *within* the ten categories that I study in this paper; for example, by buying cheaper varieties of food products. I do not have access to more detailed expenditure patterns in the US to rule this out. However, Jaravel and O'Connell (2020) explored this possibility using supermarket scanner data in the UK (with prices and quantities at the product level) and found a similar increase in Covid inflation with both fixed-basket and chained price indices (which adjust the expenditure basket over time). Their result suggests that there was little within-sector expenditure switching during the first few months of the Pandemic, at least in countries like the UK.

Furthermore, there are other Covid-related measurement challenges at lower levels of aggregation the could reinforce the *downward* bias in the CPI. In particular, Diewert and Fox (2020) and Soloveichik (2020) describe the *disappearing goods* bias, which occurs when some products' prices are no longer available to construct elementary price indices, at the most disaggregated level of the CPI. In fact, the BLS reported that the share of products with missing prices in the US CPI rose from 14% in April 2019 to 34% in April 2020. In part, this reflects the challenges of collecting data during this period (the BLS suspended physical data collections in March), but some prices are likely missing due to the stock-outs that resulted from the surge in panic-buying and supply disruptions caused by the Pandemic.[20] Diewert and Fox (2020) note that the out-of-stock products are likely to have higher market-clearing prices than those for continuing goods, potentially introducing an additional downward bias on the measured CPI that reinforces the results in my paper. For the UK, Jaravel and O'Connell (2020) estimate that the reduction in product variety due to Covid is equivalent to approximately 0.85% additional inflation. Another potential source of CPI bias was the change in promotional activity. NSOs often exclude promotions from their calculations. To the extent that promotions fell during the Pandemic, the CPI would be further downward biased. Indeed, Jaravel and O'Connell (2020) show that a decrease in promotional activity in the UK resulted in a significant surge in inflation as measured by scanner data.

[20] See Bureau of Labor Statistics (2020)

Finally, the Pandemic is also likely to introduce an *outlet* bias, as a large share of total spending moves online. Cavallo (2017) shows that multi-channel retailers tend to have identical prices offline and online, so the data collected for this type of retailer are not likely affected. However, the use of online delivery platforms such as Instacart and Shipt in the US, has soared during the Pandemic. Most of the retailers participating in these platforms disclose that they have higher prices than in their physical stores.[21] If this is not accounted for in the data sampling methodology used by the NSO, the change in outlets could introduce another downward bias in the CPI, reinforcing the results in my paper.

6 Conclusion

There is growing awareness among academics, central bankers, and statisticians about the challenges of measuring and interpreting inflation data during the Pandemic.[22] A major concern is that consumption patterns are greatly affected by large shocks, such as those induced by lockdowns and social-distancing behaviors, introducing a potential bias into the measurement of inflation with traditional fixed-basket CPIs.

Using estimates of the changes in consumer spending during the Pandemic, obtained from credit and debit card transactions by Chetty et al. (2020) and Carvalho et al. (2020), I study the impact of Covid expenditure baskets on CPI inflation in 20 countries. In 13 of those countries, I find that the Covid price index has more inflation than the official CPI. In the US, the impact was most significant in the first three months of the Pandemic, because consumers spent more on food and categories experiencing inflation, and less on transportation and related categories with significant deflation. By May, the US annual inflation rate was 0.95% with the Covid basket, compared to only 0.13% with the official CPI. The difference narrowed in the following months, but by December the Covid CPI still had 0.41% higher annual inflation. Furthermore, I show that the Covid basket bias was also present in the US Core CPI, because consumers were spending less on non-energy transportation and recreation categories. More importantly, I find that Covid inflation affected low-income households the most, leading to a sudden increase in inflation inequality in the first months of the Pandemic.

These results have important implications for policy-makers. First, they imply that the cost

[21] See Instacart (2020) and Shipt (2020)

[22] See Diewert and Fox (2020), Tenreyro (2020), Lane (2020), and Wolf (2020).

of living for consumers was higher than what was measured by the official data. The welfare implications are more relevant for lower-income households, and extend to many countries, particularly those experiencing a divergence in sectoral inflation rates. Second, my results could help explain the sudden increase in consumer inflation expectations, as reported in the Michigan Survey of Consumers for the US.[23] This is consistent with a recent literature that finds that consumers use their own purchasing experiences to form expectations about future inflation, as in Coibion and Gorodnichenko (2015), Cavallo et al. (2017), and D'Acunto et al. (2019). Third, my results highlight the fact that inflation has been relatively stable in this crisis, particularly when we take into account the changes in expenditure patterns. This supports the view that supply disruptions are putting upward pressure on prices in many sectors, compensating for the effects of the negative demand shocks. Understanding the pricing impact of these supply shocks is likely to be an important area for future research on Covid inflation dynamics.

More generally, my results suggest that the public availability of high-frequency expenditure data may give NSOs an effective way to build alternative price indices that can adjust to sudden changes in consumption patterns, significantly improving inflation measurement during times of crisis.

[23] See Curtin (2020)

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