Shock determination in a two-stage decision-making model: The case of COVID-19 in Colombia

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The contributions of this paper are as follows: (a) proposing a two-stage model to study whether an event has temporary or permanent effects on the probability of choosing a good within a market basket that traditional decision theory cannot explain and (b) studying the effects of COVID-19 on consumers’ decisions in Colombia. Findings suggest that the pandemic has transitory effects on preferences in the short run. If it lasts longer, it could induce to permanent changes. Thus, this model can be used to analyze the temporary or permanent effects of any event, regardless of its nature or geographical region, on consumer’s decision.

1 | INTRODUCTION

According to the Colombian Ministry of Health and Social Protection, the first confirmed case of COVID-19 appeared in Colombia on March 6, 2020.1 Afterwards, cases began to grow very rapidly, and 15 days later, there were almost 200 cases.2 Even though the number of cases was still relatively low, President Duque imposed a mandatory lockdown beginning March 24 that was supposed to last 19 days but was later extended several times until June 1st when some flexibilization began.3 Despite rising numbers of positive cases above 30,000 and an accumulated of more than 900 deaths,4 the government began to relax the mandatory lockdown with the purpose of allowing some economic activities (such as construction, local transportation, and freight) to return to regular operations.5 Individuals under risk conditions had to continue with the confinement while ground and air transportation of passengers between cities were still restricted.6 Next, positive cases and fatalities rose to a peak on the August 19, 2020 with 13,056 new daily cases and 16,007 deaths in total. Finally, after August 31, 2020, Colombia entered a stage of selective isolation, social distancing, and individual responsibility.8

Nowadays, as many other countries, Colombia has faced two more waves of the pandemic, being the last the one that has left more fatalities. According to data extracted from the Our World in Data organization,9 until August 25, 2021, the death toll have passed over 124,000 and positive cases have risen to nearly 4.9 million. However, during the last months, these numbers have dropped significantly, which might be attributed to the vaccination program that began in mid-February 2021.

The pandemic brought significant changes not only in terms of life losses and health problems but also in economic terms. It has caused a worldwide recession because of the conjunction of three economic shocks (Triggs & Kharas, 2020): supply, demand, and financial. The COVID-19 produced factory closures in China and everywhere else that lead to a disruption in the supply chains of parts, raw materials,
commodities such as oil, and goods and services (Gil-Alana & Monge, 2020; Goel, Saunoris, & Goel, 2021; Maital & Barzani, 2020; McKibbin & Fernando, 2020; Weder di Mauro, 2020), and unemployment (Brinca et al., 2020). This created shortages of goods and services, increased up to some extent undergroun economic activity as suggested by Berdiev et al. (2021), and, as a result, prices began to rise. On the demand side, falling exports, consumers cutting back on their spending, and firms reducing capital goods purchases and residential investment, among others, caused a significant Gross Domestic Product contraction and a downward pressure on the price level. From the financial side, the COVID-19 shock transformed into a financial crisis that caused tight financial conditions and serious balance of payments problems in fragile economies. Small and medium size enterprises had trouble to survive the squeeze on cash flows and were forced to reschedule bank loans or to default (Triggs & Kharas, 2020). Although overall economic activity declined, the most affected sectors were aviation, tourism, and leisure and hospitality (Maital & Barzani, 2020; Weng & Wai-Ming, 2021).

The COVID-19 shock caused fear and panic. These spread out among consumers distorting regular consumption patterns and some market anomalies (McKibbin & Fernando, 2020). For instance, even before having the first case of COVID-19 in Colombia, people began making in advance nervous purchases of food (mostly durable goods), hygiene and personal care stuffs, home cleansing products, and health related commodities such as antiseptic alcohol, acetaminophen, cough relief, and other over the counter pharmaceutical products. From traditional microeconomic theory, those decisions are not rational at all. Those were triggered by a stochastic shock. In this sense, we want to understand the effects of COVID-19 pandemic on consumers’ preferences and decisions. Accordingly, we extend the work of Acevedo et al. (2021) and propose a two-stage decision making model to help us provide an explanation of the nature of such apparent irrational decisions using aggregated data for consumption from Colombia. We argue that depending on the duration and how the COVID-19 shock affects the probability of choosing a given good within a market basket, the effects on consumers’ preferences could be temporary or permanent.

Since Simon (1947) introduction of the bounded rationality concept, behavioral economists (Kahneman & Frederick, 1979; Kahneman & Tversky, 1972; among others) started to investigate and demonstrate that sometimes agents do not make rational decisions as stated by traditional microeconomic models (Alchian, 1950; Ariley, 2010a, 2010b; Armstrong et al., 2020; Bauer & Capron, 2019; Cristofaro, 2020; Denes-Raj & Epstein, 1994; Simon, 1959), in the sense that some of their decisions respond to an addictive/habit-forming behavior (Laibson, 2001), relate to time and risk preferences (Soofi et al., 2020) and/or respond to searching costs (Baumol & Quandt, 1964). These developments suggest that decision-making does not derive from a single entity, but from a complex system of entities (Brocas & Carrillo, 2014), giving, thus, relevance to the initial experiments carried out by Schneider and Shiffrin (1977a, 1977b) who proposed the dual decision theory whose foundations lay on what has been called in Psychology dual decision models (Brocas & Carrillo, 2014).

Dual decision theory refers to models that have the common assumption that there are two kinds of processes influencing the human mind: controlled, reflective, or rational (cognitive system), on one side, and automatic, impulsive, reflexive, or experiential (affective system) on the other side (Alos-Ferrer & Strack, 2014). Dual decision theory argues that decision making is based on the interaction between these two processes. Some suggest that these two processes work in parallel and sometimes cooperate but at other times get into conflict. If both processes cooperate in parallel, the automatic or impulsive process becomes a tool to classify the processes rather than a crucial feature of decision conflict, as seen in the seminal works of Slovan (1996) and Epstein (1994). The deliberative or controlled process becomes important (cooperates) if an individual is unable to reach a decision using the automatic or impulsive process (see Botvinick et al., 2001; Dhar & Gorlin, 2013). Nevertheless, there could be cases when the parallel work between these two processes leads to conflict. In this condition, time becomes an important variable and, consequently, the automatic or impulsive process (the affective system), which is much faster, allows the agent to make a decision, probably induced by cognitive load memory depletion, and time pressure that the cognitive system demands (Baddeley, 1986; Dhar & Gorlin, 2013). In either case, it can be seen that the parallel work between these two systems becomes a two-stage model, where both processes could work sequentially. The deliberate or controlled process starts after the automatic process fails to find an optimal solution to the decision-making problem. It is not that the cognitive system turns the automatic process off (although the former might override the later’s response), but the deliberate or controlled process joints the automatic process and work together to reach a decision. (Dhar & Gorlin, 2013; Kahneman & Frederick, 2002).

Acevedo et al. (2021) show that in cases where the controlled or cognitive and the impulsive or automatic processes do not help the consumer reach a decision, then choice would depend fundamentally on a stochastic or random shock. We think that their model might have some important implications. For instance, in the real world, and after an initial setting process, consumption preferences of an individual tend to remain relatively constant as long as prices, income, and human factors remain fixed or invariable. However, it is possible to see that there might be random shocks that could temporarily affect his/her consumption patterns (changing the composition of the market basket, for instance). According to traditional microeconomic models, such changes in consumption patterns would not be rational. However, as time advances, new information comes at hand and the individual can determine whether or not the effects of the shock would be temporary or permanent. As a result, temporary shock effects will vanish and the consumption pattern will return to the original levels; however, permanent shock effects will change the individual preferences, his/her future consumption pattern, and optimal choice. Therefore, our contribution to the literature relies on the model that we are presenting. We apply it by using data for consumption from Colombia because of its availability. We also believe that this model could be used to study, not just the pandemic, but any other event that causes significant changes in decision making, for...
instance, natural disasters, terrorist attacks, or personal events\textsuperscript{11} regardless of geographical location.

Lastly, this article is organized as follows. In Section 2, we present the extension of the Acevedo et al. (2021) model and derive the economic, mathematical, and probabilistic implications of computing the shock probability size. Section 3, describes the data, presents the empirical evidence, and analyzes the results and their implications. And, finally, Section 4 concludes.

2 | THE MODEL

The model we are proposing differs from Acevedo et al. (2021) by having two components: a static and a dynamic part. The static part is a two-stage decision model where the first component is based on traditional economic theory (the cognitive system) and an individual human factor composed of the learning process, free will, and other human factors (the affective system). The second component refers to the stochastic shock as the determinant of decision making. The dynamic part, that allows us to understand the decision-making process along time, can be extended from Acevedo et al. (2021). We are also assuming that, despite using a dynamic model, we do not consider the concepts of present value nor try to predict the consumer decision. Instead, we try to identify what would happen to the probability of choosing a given good within a market basket that would change preferences and optimal selection. This will allow us to see whether the effects of the shock are temporary or permanent.

2.1 | The static model

We begin by considering traditional consumption microeconomic theory. Suppose there is a consumer that has preferences over a set of consumption possibilities \( X \subset \mathbb{R}_+^n \), where \( n \in \mathbb{N} \) is a given number of goods. Suppose also that those preferences satisfy the axioms of completeness, transitivity, strict convexity, and monotonicity.

Let \( x = (x_1, x_2, x_3, \ldots, x_n) \) be a vector that represents a consumption basket where \( x \in X \) and \( x_i \), for \( i = 1, 2, \ldots, n \), represents the quantity of good \( i \). Let \( x' \in X \) be another consumption basket, \( p = (p_1, p_2, p_3, \ldots, p_n) \gg 0 \) the vector of prices of the \( n \) goods, and \( M \in \mathbb{R}_+ \) the fixed consumer’s income. And, finally, let \( U = U(x) : \mathbb{R}_+^n \rightarrow \mathbb{R}_+ \) be a utility function that describes the individual’s preferences over set \( X \).

Given the factors that define the affective system, under the assumption of utility maximization (cognitive system) a consumer will select \( x \) over \( x' \) if and only if \( U(x) \geq U(x') \) and \( px = M \). Within this context, the cognitive system cooperates with the affective or automatic system and, thus, the consumer is able to come up with a decision.

From traditional microeconomic theory, this is a rational decision.

Nevertheless, as has already been demonstrated by models in the field of behavioral economics (see Kandori et al., 1993; Young, 1993) and game theory (see Weibull, 1995), human decisions do not always derive from rational analysis (see Alchian, 1950; Simon, 1959). Acevedo et al. (2021) argue that the interaction between the cognitive system, the affective system, and other random human factors may influence a consumer’s decision. As explained in the previous section, the selection of \( x \) over \( x' \) might in fact turn into a stochastic process every time a consumer must make a decision and, as a result, he/she could end up selecting \( x' \) over \( x \) and \( x' \). As pointed out, this would depend on the presence and size of shocks that might affect the probability of selection of each good within a market basket.

2.2 | The dynamic model

In this paper, we deviate from Acevedo et al. (2021) by considering not the process of selecting \( x \) over \( x' \), but the probability of selecting a \( x_i \) in a market basket \( x \). Suppose that \( x_j \) is a random variable such that its collection \( \{x_j : t \in \mathbb{N}_0\} \) can be understood as a stochastic process with a discrete parameter space (time) and a discrete state space \( \{x_i\}_{i=0}^n \). Obviously \( \sum_{i=0}^n Pr(x_i) = 1 \) for all \( t \in \mathbb{N}_0 \), by the natural definition of this random process of choice. Based on the proposition of Acevedo et al. (2021), we have:

\[
Pr(x_{ij}) = Pr(x_{i-1j})Pr(\varepsilon_{t-2i}) + Pr(\varepsilon_{ij}),
\]

where \( Pr(x_{ij}) \) is the probability of choosing \( x_i \times x' \) at time \( t \); \( Pr(x_{i-1j}) \) is the initial probability of selecting \( x_i \) at period \( t \), which is the probability of selection of \( x_i \) in \( t-1 \); \( Pr(\varepsilon_{t-2i}) \) is the average of the probabilities of shocks from \( t-j \) up to \( t-2 \) (with \( j \geq 3 \)) that collects information about the positive and negative feelings toward good \( i \); and \( Pr(\varepsilon_{ij}) \) is the probability that a shock not considered elsewhere affects consumption.

At \( t = 1 \), the individual does not have any positive or negative feelings from the cognitive and affective systems whatsoever toward good \( i \). Then, let us assume that \( Pr(\varepsilon_{t-2}) = 0 \) and \( Pr(x_{0i}) = 0 \). As a result, from Equation 1, we obtain

\[
Pr(x_{ij}) = Pr(\varepsilon_{ij}).
\]

At \( t = 2 \), given that \( Pr(x_{i-2j}) = Pr(x_{0j}) = 0 \), Equation 1 turns into

\[
Pr(x_{ij}) = Pr(\varepsilon_{ij}).
\]

This means that during the first two periods, contemporaneous shocks dominate and decision making is a stochastic event. This happens because we are assuming that it takes time for the individual to consider information from the past, to learn, and to make decisions. Nevertheless, at \( t = 3 \)

\[
Pr(\varepsilon_{t-2i}) = \frac{Pr(x_{ij})}{1} = Pr(\varepsilon_{ij}),
\]

and thus Equation 1 changes to
Now, let us focus on the term \( \Pr(x_{t-2}) \) from Equation 1. Then, at \( t = 4 \),

\[
\Pr(x_{t-2}) = \frac{\Pr(x_1) + \Pr(x_2)}{2},
\]

at \( t = 5 \)

\[
\Pr(x_{t-2}) = \frac{\Pr(x_1) + \Pr(x_2) + \Pr(x_3)}{3},
\]

and, in general,

\[
\Pr(x_{t-2}) = \frac{\Pr(x_1) + \Pr(x_2) + \ldots + \Pr(x_{t-3}) + \Pr(x_{t-2})}{t - 2}
= \frac{\sum_{i=1}^{t-2} \Pr(x_i)}{t - 2}.
\]

Every time an event or innovation occurs, the value of the shock changes and affects the probability of choosing \( x_{ij} \) in \( \text{x} \). Consequently, it modifies consumer preferences and choice. If the innovation is temporary, the new value of the probability of the shock will remain changed while the event lasts. When the event ends, the probability of the shock returns to the state before the event. If the event is permanent, then the change in consumer preferences is permanent.

The recursive effect shown in Equation 4 will be reflected by the difference between probabilities before and after the event. The new information that an event brings affect the cognitive and affective system up to two periods after. Thus, \( \Pr(x_{t-2}) \) will be determined by the average of the shocks from the preceding periods as shown previously.

Therefore, Equation 1 can be written as

\[
\Pr(x_{ij}) = \Pr(x_{t-1}) \frac{\sum_{i=1}^{t-2} \Pr(x_i)}{t - 2} + \Pr(x_{ij}),
\]

where \( \Pr(x_{ij}) \in (a, b) \) for all \( t \in \mathbb{N} \), such that (a, b) with a < b is a probabilistic confidence interval.\(^{14}\) Now, from Equation 5, let us solve for \( \Pr(e_{ij}) \).

\[
\Pr(e_{ij}) = \Pr(x_{ij}) - \Pr(x_{t-1}) \frac{\sum_{i=1}^{t-2} \Pr(x_i)}{t - 2}.
\]

Equation 6 implies that we could identify the size of the probability of the shock on a given good at any time if we have information about past shocks and initial and current probabilities of choosing \( x_{ij} \).

In order to keep the model as simple as possible, let us write Equation 6 in a more compact form:

\[
\Pr(e_{ij}) = P_{ij} - P_{t-1} \left[ \frac{\sum_{i=1}^{t-2} \Pr(x_i)}{t - 2} \right],
\]

where \( P_{ij} = \Pr(x_{ij}) \) and \( P_{t-1} = \Pr(x_{t-1}) \). As shown above, Equation 7 is a recursive system whose solution is given in terms of probabilities. This is the equation that we will use to compute the probability of the shock on each good. Obtained this way, \( \Pr(e_{ij}) \) is the size of the probability from the shock that we believe affects the probability of selecting good i in market basket x.

Before discussing our results from the previous sections and their empirical applications, it is important to describe the general structure of the shocks in terms of probability theory. Let \( S \) be a given random event that might affect consumer preferences. If \( a_i \) is a binary variable that takes the value of 1 when the event occurs and 0 otherwise, then it is possible to write the magnitude of the probability of the shock at time \( t \) as:

\[
\Pr(x_t) = \frac{1}{C_0} \left( \eta_1 \Pr\left( e_{t,1}^{(1)} \right) \right) + (1 - \eta_1) Pr\left( e_{t,1}^{(0)} \right),
\]

where \( \Pr(x_t) \) is a random element such that \( \Pr(e_{t,1}^{(1)}) \) is the value of the shock probability when the event happens, \( \Pr(e_{t,1}^{(0)}) \) when it does not, and \( \eta_1 \) is a correction parameter that takes values within the semiclosed interval \( (0, 1) \). Therefore, in consecutive periods \( t - 1 \) and \( t \) during which there is no event that affects the individual preference patterns, it is expected that

\[
\Pr(e_{t,1}^{(1)}) - \Pr(e_{t,1}^{(0)}) = 0.
\]

This implies that when the shock occurs the probability of affecting the selection of \( x_{ij} \) is zero. Therefore, there are no reasons for a consumer to change consumer preferences if the expected probability that a shock might affect her behavior is zero; that is, expected preferences and optimal choice would not be affected. Another way to look at these results is in terms of the first difference of the probability of the shock. If there is no event that affects the individual preferences, we would expect that

\[
\Pr(e_t) = \frac{1}{C_0} \left( \eta_1 \Pr\left( e_{t,1}^{(1)} \right) \right) + (1 - \eta_1) Pr\left( e_{t,1}^{(0)} \right).
\]

As a result, this implies that \( e_t - e_{t-1} \equiv 0 \) and guarantees that the proposed random element is well defined. However, if at time \( t \), a shock occurs then

\[
\Pr(x_t) = \Pr(x_t) - \Pr(x_{t-1}) \neq 0
\]

and

\[
\Pr(x_{t-1}) = \Pr(x_t) - \Pr(x_{t-1}) \neq 0,
\]

which implies the event might have transitory effects (with changes only in the short run) or permanent effects (that will change consumer preferences in the long run).

As we have seen, the results of our model imply that shocks could play an important role in consumption decision making, could affect consumption patterns, and could modify the consumer preferences. These results would depend on the size of the shock’s probability. In the next section, we use real consumption data from Colombia to compute the probabilities of the shock on good i being selected in a market basket.

### 3 | EMPIRICAL EVIDENCE: THE COVID-19 SHOCK IN COLOMBIA

To carry out the computation of the magnitude or size of the shock in probability terms, we use aggregate monthly data from Colombia,
supplied by RADDAR Consumer Knowledge Group, for the period of January 2017 to July 2021 (in billions of Colombian pesos)\textsuperscript{15} for each one of the following consumption groups: (1) Food; (2) Housing; (3) Clothing and Footwear; (4) Healthcare; (5) Education; (6) Culture and Leisure; (7) Transportation and Communications; and (8) Other Expenditures. We use data for Colombia because these are what we have at hand and not because Colombia is a special case. There are indeed data on consumption in other countries but we do not have access to those.

Given that we do not have individual data, we use aggregate data to carry out the calculation of a shock probability of $x_i$ being chosen in a market basket. In this sense, we assume that this group of consumption series conforms an average market basket. Thus, let us suppose these data reflect consumption patterns of an average Colombian citizen and let us suppose that such decisions are optimal.

Because of data availability and the way we built our model, the first two periods of the computed probabilities of the shock will have significant variability. Inspection of Equations 2 and 3 helps clarify this issue. It happens by construction. It is like the individual begins life at period 1, that is in January 2017 but it takes up to 2 months to form expectations (positive or negative feelings) toward good $i$. We impose this assumption to keep the idea of our model as clear as possible.

Figure 1 shows the natural log for each expenditure group of the raw data. According to Figure 1, the bulk of total spending is represented by food, housing, transportation and communications, and other expenditures while clothing and footwear and culture and leisure are the items that represent the lowest proportion of household expenditure. Besides, it is possible to observe the impact of COVID-19 after February 2020 (see the vertical line in the graph\textsuperscript{16} and the effects of the lockdown that were imposed during March, April, and

\textbf{FIGURE 1} \quad \text{Original series—natural log scale}

\textbf{FIGURE 2} \quad \text{Original series under seasonal adjustment—natural log scale}
May by the national government to contain the pandemic. We can also see the effects of a major political strike (paro nacional) that took place at the end of April 2021 and that lasted several weeks. With respect to the COVID-19 event, notice the negative effects on transportation and communications, culture and leisure, and clothing and footwear, and the positive effects on healthcare. Another aspect that deserves special attention is the seasonality presented in the data, particularly in the mid and the end of each year when workers receive a special bonus called “la prima.”

In order to carry out the computations using data without seasonal effects, we use the classical method of Tramo-Seats under E-views versión 7.0\textsuperscript{17} to de-seasonalize the data. This procedure allows to maintain the structure, in terms of averages and variability, of the consumption set time series within the period of study. Figure 2 shows the logs of the de-seasonalized series. The graph is neat and shows more clearly the effects we mentioned previously.

To carry out the calculations, as suggested by Equation 7, we proceed as follows:

a. We use the classical criteria of frequencies to compute probabilities. That is, we compute the relative frequency of each expenditure group in total consumption for every month of the time span. We define these frequencies as final probabilities.

b. By means of Equation 7, we estimate the size of the probability of each shock (stochastic shocks) and its corresponding time series (see Figure 3).

c. At last, we standardize the probabilities of the shock on each item to make comparisons among them and determine what group of goods and services were the most affected by the pandemic. In this manner, we would be able to see the short run effects on consumption patterns and whether these changes would affect preferences in the long run. Likewise, we estimate the first difference of

\[\text{FIGURE 2} \quad \text{Stochastic shocks—time series}\]

\[\text{FIGURE 3} \quad \text{Stochastic shocks—standardized probabilities}\]
The shock’s series to show their dynamic impact on the shock probabilities. These results are shown in Figures 4 and 5.

Inspection of these figures shows some interesting findings around the estimated shocks. Firstly, notice that each series presents significant variability in the first periods. As mentioned before, it happens by data availability and the way we build our model. It is like the agent begins to live in the first period (first month) and takes up to two periods to learn and adjust his/her consumption patterns (optimal choice). The most abrupt changes occur in those series that represent the bulk of the market basket expenditures. Second, we observe that, after the first months of adjustment, consumers define their preference patterns and probabilities remain on a path of relative constant average and variance. No need to say that in these first two stages, all possible deterministic events that might influence individuals’ consumption tend to be more relevant that random events, particularly in the second stage where serial transitions are smoother for all the components considered in the analysis. Finally, when COVID-19 occurs (the third stage), we notice that the magnitude of the probability changes significantly indicating a remarkable shift in consumption patterns. These probabilities return, after some months, to magnitudes similar to those observed in the second stage.

Figure 4 shows that, effectively, the pattern of preferences is well defined as long as there are not significant shocks. However, once the event of COVID-19 happens, consumers obviously increase consumption in items such as food, housing, healthcare, and other expenditures, while reduce spending on transportation and communications and culture and leisure.

Returning to Figure 3, it displays that each shock probability follows approximately a normal distribution. This happens because this asymptotic fact is linked to the levels of asymmetry observed both in the first stage of learning as well as during the event of COVID-19. Additionally, according to our estimates, it is very interesting to see that six or 7 months after the initial effect of COVID-19, on a probabilistic average, the shock probability for the food component of the market basket returns to magnitudes observed in the second stage. The same occurs for housing, education, and transportation and communications, respectively. This means that COVID-19 causes temporary effects on those components. The series returned to the same average or center of gravity that had reached before COVID-19. However, this average asymptotic behavior is not observed in the components of clothing and footwear, healthcare, other expenditures, and culture and leisure, even when flexible lockdown began on the first day of June. For these components of consumption, according to the data for Colombia. According to the behavior or these probabilities, it looks like Colombian consumers felt that COVID-19 effects might be permanent.

What we observed in Figures 3–5 can also be explained in terms of basic descriptive statistics and unit root tests. Table 1 shows that food, housing, education, and transportation and communications are stationary white noise (non-Gaussian). These tests indicate that the series for those components had returned to their long-run equilibrium and it is expected that these series will not change abruptly in a certain period, unless the economy is affected by another important shock, such as a significant reoutbreak of the pandemic. Nevertheless, the rest of the components are non-stationary, indicating that the series of shocks will not return to their long-run equilibrium. Finally, the major implication that these results show is that, with COVID-19, consumption patterns in relative terms have changed, suggesting that consumer preferences have also changed over time. This result goes hand in hand with our main theoretical result. Temporary shocks affect optimal choice in the short run; however, preferences can be affected by shocks in the long run only if the effects of the shock tend to be permanent.

**Figure 5** Stochastic shocks—first differences

| Components                  | 01/01/2018 | 01/01/2019 | 01/01/2020 | 01/01/2021 |
|-----------------------------|------------|------------|------------|------------|
| Food                        |            |            |            |            |
| Housing                     |            |            |            |            |
| Clothing & Footwear         |            |            |            |            |
| Healthcare                  |            |            |            |            |
| Education                   |            |            |            |            |
| Culture & Leisure           |            |            |            |            |
| Transportation & Communications |        |            |            |            |
| Other Expenses              |            |            |            |            |
TABLE 1  Descriptive statistics and basic tests for the random shocks

| Shock                         | Mean, variance | Jarque–Bera statistic | Ljung–Box statistic | ADF test (a)     | ADF test (b)     | ADF test (c)     |
|-------------------------------|----------------|-----------------------|---------------------|------------------|------------------|------------------|
| Food                          | 0.2491         | 172.497***            | 18.529              | −0.876           | −5.360***        | −6.089***        |
|                               | 0.0186         | (0.000)               | (0.777)             | (0.332)          | (0.000)          | (0.000)          |
| Housing                       | 0.1914         | 466.878***            | 14.306              | 0.026            | −6.300***        | −5.057***        |
|                               | 0.0102         | (0.0000)              | (0.939)             | (0.687)          | (0.0000)         | (0.0070)         |
| Clothing and footwear         | 0.0260         | 33.907***             | 108.540***          | −0.632           | −2.087           | −2.563           |
|                               | 0.0033         | (0.000)               | (0.000)             | (0.438)          | (0.251)          | (0.298)          |
| Healthcare                    | 0.0459         | 140.174***            | 67.462***           | −0.204           | −1.910           | −1.854           |
|                               | 0.0026         | (0.000)               | (0.000)             | (0.608)          | (0.325)          | (0.664)          |
| Education                     | 0.0516         | 138.916***            | 13.773              | 0.224            | −7.404***        | −8.877***        |
|                               | 0.0013         | (0.000)               | (0.952)             | (0.747)          | (0.000)          | (0.000)          |
| Culture and leisure           | 0.0289         | 80.535***             | 116.200***          | −0.621           | −2.473           | −2.181           |
|                               | 0.0045         | (0.000)               | (0.000)             | (0.444)          | (0.128)          | (0.1878)         |
| Transportation and communications | 0.1394        | 555.9705***           | 30.179              | −0.7754          | −3.8638**        | −4.041**         |
|                               | 0.0140         | (0.000)               | (0.179)             | (0.377)          | (0.004)          | (0.013)          |

Note: Null Hypothesis Ho for Jarque–Bera Statistic: “The series has a normal distribution.” Null Hypothesis Ho for Ljung–Box Statistic: “The series does not have temporal autocorrelation.” (a) ADF Test without constant and linear trend (lt). (b) ADF Test with constant. (c) ADF Test with constant and lt. Null Hypothesis Ho for ADF Test: “The series has a unit root (is not stationary).” * p values are in parentheses.

Abbreviation: ADF, augmented Dickey–Fuller.
**Significance at the 0.05 level.
***Significance at the 0.01 level.

4  | CONTRIBUTIONS AND CONCLUSIONS

Currently, the health, economic, social, cultural, and political impact of the COVID-19 pandemic has been widely studied. From multilateral organizations such as the United Nations (UN), World Health Organization (WHO), Food and Agriculture Organization (FAO), International Labor Organization (ILO), the International Fund for Agricultural Development (IFAD), the World Bank Group, government finance departments or ministries, health national institutes, central banks, pharmaceutical laboratories, research centers, to universities, all have dedicated efforts to comprehend and lessen the effects of COVID-19. For instance, the works of Berdiev et al. (2021), Goel, Nelson, and Goel (2021), Barro et al. (2020), Ludvigson et al. (2020), Chudik et al. (2020), and McKibbin and Fernando (2020), to mention some, have studied the impacts of COVID-19 on the global economy and other impacts such as on corruption and underground economy. However, in this work, we take a different path. We want to analyze the effects of COVID-19 in microeconomic terms by studying consumer behavior and decision making using data for Colombia. Particularly, we proposed a dynamic two-stage decision-making model in which a random shock (such as the pandemic) affects choice and preferences. By computing the size and behavior of probability of shocks over time, it was possible to determine, on average, how the composition of market baskets was affected and whether these changes were reversed to their long-run equilibrium. Our hypothesis was that if consumption patterns returned to the paths observed before the pandemic, then the effects of the shock would be transitory and there would not have had changes in preferences. Otherwise, consumers’ preference change would be permanent. Thus, our paper contributes to the literature by proposing a model that helps us understand the impact of any event and demonstrates that shocks are important determinants of consumer behavior. Particularly, the model presents one way to study whether the event has temporary or permanent effects on the probability of goods being chosen within a market basket. As a result, consumption patterns might be affected not only in the short but also in the long run suggesting that choice, under some circumstances, might not be optimal from the viewpoint of traditional decision theory.

The evidence shows the path toward measuring one of the different ways that COVID-19 has impacted consumers’ choice and preferences. First, there have been changes in consumption of goods and services such as food, housing, education, and transportation and communications that were impacted at the time the event originated but that have returned (by July 2021) to their long-run equilibrium. Second, we have items such as clothing and footwear, health, culture and leisure, and other expenditures affected by the COVID-19 event that have not yet returned to their steady-state values or long-run equilibrium even when the Colombian economy has practically returned to the activity before the pandemic. In terms of preferences, consumers are still expectant about how events will develop in the next months. That is, COVID-19 still continues to generate great uncertainty on consumers when making decisions about their consumption. Decisions that look irrational from the perspective of traditional economic models, at the time the pandemic appeared for the first time in Colombia are now not so irrational at all. However, this is an area that requires more research and, even when vaccination programs have been carried out, still there is no certainty about the pandemic duration and how much time consumers need to adjust to the pandemic so that everyone feels safe in this new normality.
The model we are proposing can also be used to study consumers’ decision-making in other countries. Even though our findings are the result of the application of our model for Colombia, the model could be used to study the effects on preferences and decision making of any event such as the recent coup d’état in Myanmar, the tsunami of Indonesia of 2004, the hurricane Katrina of 2005, the terrorist attacks of 9/11, or even a more global historical event as the Spanish flu. The only limitation for any application would be data availability.

Additionally, our results can provide a suggestive evidence and guidance to policymakers and decision-makers of the supply side. Brinca et al. (2020) state that aggregate demand shocks could be offset by conventional monetary and fiscal policy. However, the pandemic can have two different type of aggregate shocks: demand and supply. Then, for the specific case of Colombia, policymakers used traditional fiscal and monetary policies to respond to the pandemic shock and the economy has responded with a slow recovery. Nevertheless, as pointed out by Brinca et al. (2020) they could have considered different policies to offset these shocks, i.e. the liberalization of trade policies and the de-bureaucratization of permits that would allow the supply chain logistic optimize their efficiency. These could have two effects. First, the market would have enough stock of the more demanded good and services, and second, as Goel, Saunoris, and Goel (2021) demonstrated, having a reliable supply chain could slow down the negative effect of the pandemic on economic growth and recovery could be faster. In this sense, there are still some unanswered questions: can aggregated shocks of supply and demand be measured following a similar methodology? What are the public policy implications of the COVID-19 shock? And can Colombians and Colombia return back to their pre-COVID-19 preferences and economic performance? These are questions that will be addressed in further research.

At last, it is important to point out at least one limitation of our paper: not having access to more and current data. In this study, we use 55 monthly observations for groups of products in a market basket from January 2017 to July 2021 for the Colombian economy. Further research should take into account more disaggregated data and for a much longer time span. However, it is important to keep in mind that having a longer time span might introduce noise coming from other events, such as the relative effectiveness of vaccination programs, the mass use of the internet, policy shocks, or other economic, political, or social phenomena.

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DATA AVAILABILITY STATEMENT

The data on consumption that supports the findings of this study are available from RADDAR, but restrictions could apply to the availability of these data. Data were used under permission of RADDAR for the current study and authors do not have the right to share it. Data are however available from the authors upon reasonable request and with the permission of RADDAR.

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ENDNOTES

1 See https://www.minsalud.gov.co/Paginas/Colombia-confirma-su-primer-caso-de-COVID-19.aspx and decree 457. https://dapre.presidencia.gov.co/normativa/normativa/DECRETO%20457%20DEL%202021%20DE%20MARZO%20DEL%202020.pdf.
2 See https://www.datos.gov.co/Salud-y-Protecci-n-Social/Casos-positivos-de-COVID-19-en-Colombia/gt2j-8ykr/data and https://ourworldindata.org/coronavirus/country/colombia.
3 https://coronaviruscolombia.gov.co/Covid19/acciones/acciones-deaislamiento-preventivo.html.
4 According to data extracted from https://ourworldindata.org/.
5 Still some restrictions applied.
6 See https://coronaviruscolombia.gov.co/Covid19/acciones/acciones-deaislamiento-preventivo.html.
7 According to data extracted from https://ourworldindata.org/.
8 See https://www.canalinstitucional.tv/noticias/colombia-no-tendra-mas-cuarentena-obligatoria-presidente-duque.
9 https://ourworldindata.org/.
10 Habit-formation could be a form of decision from the intuitive or automatic process.
11 Personal events such changes in family structure, that is, births or deaths.
12 Following Acevedo et al. (2021), pages 11–12, under the restrictions explained there about the probability of random shocks, \( Pr(\varepsilon_t) \), we made sure that Equation 1 is well defined in probability terms.
13 From here on, we assume that it takes the consumer at least two periods to form positive or negative feelings towards good \( i \).
14 If we analyze expressions 3 and 4 exclusively in terms of random variables (excluding the probability measure on these), we have that for any time \( t \), the right hand side of both is composed by the product of two fixed terms that obviously result in a fixed term at time \( t-1 \) and a purely stochastic term at time \( t \). Consequently, it follows \( \text{Cov}(X_t) = 0 \) for all \( t \in \mathbb{N} \). This implies that our model does not present temporal autocorrelation problems, despite having been constructed recursively.
15 Since we are working with data in relative terms, then we did not deflate the series.
16 As the graph shows, consumption changed since late February and early March even when the lockdown was imposed in late March. So, that is why we are assuming that the shock is stochastic. Consumption did not vary because of the lockdown. It began to change even before the first case appeared in the country.
17 https://www.eviews.com/home.html.
18 In Figure A1, we show in detail the first difference of the shock for a period of 7 months before Covid-19 hit Colombia and 7 months after the first case of COVID-19.
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APPENDIX A

FIGURE A1  Detailed stochastic shocks—First difference