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Expectation-based consumer purchase decisions: behavioral modeling and observations

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Abstract
Expectations play important roles in consumers' purchase decisions. Among many types of expectations, consumers often form expectations on future market conditions when purchasing goods or services. This study develops a multiple-selves intertemporal choice model for such expectation-based purchase decisions, incorporating behavioral factors such as present-biased preferences into the model. An analysis based on the model shows that consumers adopt a threshold perception-perfect strategy when making purchase decisions and the threshold depends on values of model parameters that capture expectations on key market conditions. Different consumers often have different parameter values, leading to heterogeneous behavior. The study further applies the model to explain observations from medical service consumption data during the COVID-19 pandemic, and shows that the expectation-based purchase model provides a sound explanation for the observed heterogeneous purchase decisions across individuals with different incomes and health insurance status.

Keywords Behavioral modeling · Multiple-selves model · Consumer purchase decisions · Consumer expectations · External market conditions · Data analytics

1 Introduction

In acquisitions of goods or services, consumers often form expectations on future market conditions, and such expectations play important roles in consumers' purchase decisions (e.g., whether or not and when to make a purchase). For example, consumers often form expectations on future affordability of goods or services and

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make purchase decisions accordingly: foreseeing inflation, consumers may prepone purchases; anticipating price drops, consumers may postpone purchases. A similar situation may occur when consumers form expectations on future availability of goods or services. This is especially evident during crises, when consumers aggressively stockpile or hoard necessities (see, e.g., Corkery et al., 2020), and during severe weather, when shoppers often raid grocery shelves (Chris, 2018). In addition, consumers may also sense risks on certain occasions, such as health risks during a pandemic and safety risks after a terrorist attack, and consequently cancel or delay their purchases (e.g., transportation service index dropped 20% after the 9/11 terrorist attacks, BTS, 2017).

Consumers' expectations on market conditions may affect different consumers' purchase decisions differently: it is likely that consumers with distinct backgrounds form different expectations, leading to heterogeneous behavior. Such behavioral heterogeneity has been witnessed by local retail managers we consulted, who stated that the COVID-19 pandemic not only affected their sales, but also changed their in-store shopper composition (i.e., the pandemic had heterogeneous impacts on different consumer groups); in fact, the comments from the local retail managers directly motivated this study. Given the significant and diverse impact of consumer expectations, it is critical to gain an in-depth understanding of how the expectations on market conditions (availability, affordability, risks, etc.) affect consumers' (possibly heterogeneous) purchase decisions.

The study of expectation-based purchase decisions entails an intertemporal choice behavioral model to capture individual consumers' expectations on future market conditions, the decision process, and possible behavioral heterogeneity. Yet, despite the research need, the subject has not been sufficiently addressed in the literature. One stream of literature studied expectations with respect to model consistency and uncertainty/ambiguity. Among the works in this literature is the well-known rational expectations theory, which, proposed by Muth (e.g., Muth, 1961) and popularized by Lucas (e.g., Lucas, 1975) and Sargent (e.g., Sargent & Wallace, 1975) (see also Galbács, 2015, Chapter 2 for a discussion), ensures internal consistency between expectations and actions at the aggregate level. Oliver & Winer (1987) provided a comprehensive review of earlier works in this literature on the expectation formation and proposed a general framework for the formation process. The expectation models in this stream of literature, focusing on future uncertainty/ambiguity and model consistency, are very different from what we aim to capture, i.e., consumers' expectations on future trends of market conditions.

Another stream of prior research developed the multiple-selves framework to study an individual's intertemporal choice. In this framework, the individual in each period is considered as a separate "self," and each self makes decisions in consideration of future selves' choices (see, e.g., the discussion in O'Donoghue & Rabin (1999)). That being said, these studies mainly applied the framework to study self-control problems where individuals form expectations on future selves' self-control capability (see, e.g., Strotz, 1955; Pollak, 1968; Laibson, 1997; O'Donoghue & Rabin, 1999). An illustrative example is that, when setting an alarm at night, an individual, knowing that the self tomorrow morning may not resist the temptation to switch the alarm off and continue the sleep, might choose to adopt some commitment technology (e.g., a snooze button) that disciplines the morning self. Our study leverages the multiple-selves framework and extends it to study expectations on market conditions, instead of self-control capability, which renders model specifics and analyses different from the prior studies. Furthermore, while the multiple-selves framework has been widely used in behavioral economics (see, e.g., Dhami, 2016 Chapter 11) and economic psychology (e.g., Jamison & Wegener, 2010), applications in marketing are scarce. Our study applies the framework to marketing applications.

In developing the multiple-selves formulation, one important behavioral factor that needs to be incorporated is present-biased preferences. Present bias refers to the fact that individuals' discount rates over time are far from time-consistent, but instead are much higher over shorter horizons (see, e.g., Thaler, 1981; Soman et al., 2005, and Dhami, 2016 Chapter 10). The modeling of present-biased preferences has been a major endeavor in the recent intertemporal choice literature, with a simple discount function, the quasi hyperbolic discounting (based on the initial work of Phelps & Pollak, 1968 and popularized by Laibson, 1994, 1997), considered having "paved the way for major applications of present-biased preferences" (Dhami, 2016, p. 38). This study thus adopts this discount function in the multiple-selves formulation.

Incorporating the aforementioned behavioral factors, we develop a multiple-selves model to capture expectation-based consumer purchase decisions. An analysis based on the model shows that a consumer adopts a threshold perception-perfect strategy when making a purchase decision: a consumer purchases a good or service after a certain threshold of time, and the threshold depends on values of model parameters that capture expectations on key market conditions. Different consumers may have different parameter values, leading to behavioral heterogeneity. To check whether the model and analysis can explain real consumer purchase observations, we compile a novel dataset on medical services during the COVID-19 pandemic and examine the purchase decisions therein. We select the pandemic period because the pandemic tends to significantly affect consumers' expectations on market conditions, rendering sharp insights. We select medical services as the field for the illustration because it is subject to relatively low confounding effects (to be detailed later). An exploration of the data shows that the pandemic lockdown more significantly delayed the medical service consumption of individuals with high incomes or with health insurance, relative to those with low incomes or without health insurance. We show that this observation can be well explained by our model.

In marketing, the related literature includes a body of empirical studies that considered consumers' intertemporal preferences. For example, Winer (1985) developed a reduced-form consumer purchase model that incorporated consumers' expectations about future prices. Song & Chintagunta (2003) developed and estimated a structural model, in which forward-looking consumers optimize purchase timings by considering their utilities from buying the product and their expectations on future prices. Nair (2007) developed a model to investigate empirically a firm's pricing policy in the presence of consumers who may delay purchases in expectation of future lower prices, and solved the model using numerical dynamic programming techniques. Dubé et al. (2014) presented a survey design to elicit intertemporal purchase decisions and identify utility and discount functions. Interestingly, the study did not find strong evidence for present-biased preferences in their data (Blu-ray player adoption). While these studies quantified consumers' intertemporal purchase behavior in different empirical contexts, we build an expectation-based behavioral model and derive analytical results and insights. To our best knowledge, our study is the first to use a multi-selves intertemporal model with quasi hyperbolic discounting to analytically capture expectation-based consumer purchase decisions. The derivation of analytical solutions allows us to clearly characterize how consumers' expectations on future market conditions affect their purchase decisions. Notably, the market conditions captured in our model are generic and not limited to certain specific factors (prior empirical studies often focused on just the price factor); the quasi hyperbolic discounting parameters in our model can assume any values, including the pure present-biased discounting and the classical geometric discounting as two special cases (see Section 4 for details); the expectation functions can assume any general forms (not necessarily a linear form; also see Section 4 for details). The analytical solution of a model with these generic features renders important insights into expectation-based purchase decisions and great potential for numerous future applications. In addition, through the behavioral modeling and observations, our study adds to the increasingly important literature of behavioral studies in marketing (see, e.g., the recent review paper by Dowling et al., 2020), as well as the recent heightened interest in the blending of theory and data in marketing research (see, e.g., Lehmann, 2020).

2 Behavioral modeling

In this section, we develop the multiple-selves model to capture expectation-based consumer purchase decisions. We consider an individual who needs to acquire a good or service over a time horizon of $T < \infty$ periods. In each period $t, t = 0, 1, ..., T$, a self of the individual needs to decide whether to acquire the good or service right now, cancel the acquisition permanently, or delay the acquisition to a later period. Acquiring the good or service in period t renders an instantaneous utility (before discounting) u_t. Canceling the purchase permanently yields a utility of 0. Let $U_t(\tau)$ denote an individual's intertemporal utility in period t when acquiring the good or service in period $\tau \geq t$ (i.e., the individual's utility from period t onward until the end of the time horizon), then we assume

$$U_t(\tau) = \begin{cases} u_t & \text{if } \tau = t, \\ \beta u_\tau & \text{if } \tau > t, \end{cases} \tag{1}$$

where $0 < \beta < 1$ is a "bias for the present" parameter in the quasi hyperbolic discounting framework. Note that a general quasi hyperbolic discounting has another time-consistent discount parameter δ, but here for simplicity, we initially follow the parsimonious formulation in O'Donoghue & Rabin (1999) and assume δ to be 1. This usually does not incur substantial loss of generality, as most literature suggests that δ is close to 1 (e.g., $\delta \approx 0.96$ as estimated by Laibson (2007) and elaborated on (Dhami, 2016, p. 651; see also Burks et al., 2012 for similar estimates).

Nevertheless, in Section 4, we will extend our analysis to the case with $\delta < 1$ (e.g., Frederick et al., 2002 reported possible δ values below 0.9) and show that the insights that we have derived remain the same. The intertemporal utility (1) means that if the individual acquires the good or service in the current period, then the individual garners the instantaneous utility for the current period; otherwise, the individual garners the discounted utility for the future period when the acquisition is made. The boundary condition is $u_{T+1} = 0$, meaning that if the individual decides not to acquire the good or service within the time horizon T, then the individual cancels the purchase. In fact, purchase cancellation is a special case of purchase postponement (to period $T + 1$) because in any period, purchase cancellation is always weakly dominated by purchase postponement (which yields a non-negative utility).

It is also worth noting that in this formulation, the present bias factor β is consistent over time (i.e., it is not β_t), meaning that a self believes that future selves will have the same present bias as that of their own. Such a setup is very common in the literature and has been adopted by studies such as Strotz (1955); Pollak (1968); Laibson (1997), and the sophisticates model in O'Donoghue & Rabin (1999). Some self-control studies allow β to be time-inconsistent to model more self-control complications. However, since our focus is not self-control, examining the time-consistent case suffices.

We next formulate the expression of the instantaneous utility u_t to incorporate an individual's expectation on market conditions. As an example, in a pandemic context, such conditions primarily concern health-related and cost-related conditions: the acquisitions of many goods or services require physical contacts, posing infection risks; the pandemic may also affect employment, leading to poor affordability for the good or service. To model an individual's expectation on market conditions, we adopt a simple linear model and assume that acquiring the good or service in period $t \in \{0, 1, ..., T\}$ renders an instantaneous reward of $a_r + b_r t$ and incurs an instantaneous cost (a combination of risk, payment, logistics, opportunity cost, etc.) of $a_c + b_c t$. The parameters a_r, a_c, b_r and b_c are specific to the specific individual and the specific good or service. However, for notation simplicity, we omit the corresponding subscripts and consider only one individual and one good or service in our model, while delaying a discussion of how different parameter values of different individuals, goods or services affect behavioral choice to later sections. It is also worth noting that although this parsimonious linear model well serves our main purpose of deriving insights into human choice with time-dependent expectations, we nevertheless consider general expectation functions in Section 4 and extend our insights therein.

Given the reward and cost, the individual's instantaneous utility for the good or service in period t is:

$$u_t = (a_r + b_r t) - (a_c + b_c t) := a + bt, \tag{2}$$

where $a = a_r - a_c$ and $b = b_r - b_c$. As an example for practical meanings of the reward and cost formulations, in the context of medical services during the COVID-19 pandemic, the reward can derive from a service's medical necessity; a lower necessity means a lower reward. The cost can include both health (infection) risk and affordability of the good or service. A very cautious individual may believe the health risk right now is too high, and thus delay the purchase. In this case, a_c can be large (i.e., the current risk is high) and b_c can be negative (i.e., the expected future risk will be lower). The more cautious the individual is about the current health risk, the larger the a_c; the more optimistic the individual is about the future health condition, the smaller the b_c. In like manner, the affordability of the good or service is often linked to an individual's financial status. An individual highly concerned about their financial instability in the future may believe $b_c > 0$, i.e., the affordability of the good or service will become poorer or the relative cost will be larger; in contrast, an individual with little financial instability concern may believe $b_c \approx 0$. The aggregated parameters a and b can be either negative or positive, representing an overall negative or positive view of the current or future conditions. As an example, an individual may have an overall negative view of the current condition ($a < 0$) and does not want to make a purchase right now. However, if the individual is optimistic about the overall future condition ($b > 0$), then the instantaneous utility may eventually justify the purchase in a future period (i.e., $u_t > 0$ for some t).

Given this multiple-selves model with the expectation formulation, an individual's choice is described by a strategy $\boldsymbol{s} = (s_0, s_1, ..., s_T)$, where $s_t \in \{Y, N\}$ specifies whether or not to make a purchase in period t given that the individual has not yet done it. Similar to a dynamic game and the corresponding subgame perfect equilibrium concept, even if the individual makes a purchase in period t (i.e., $s_t = Y$), we still need to specify what the individual's decision would be after period t (i.e., to specify $s_{t'}$ for all $t' > t$). The solution concept of this multiple-selves model is a *perception-perfect strategy*, in which the self in period t aims to make a decision to maximize the intertemporal utility U_t, expecting that the future selves will do the same. It follows straightforwardly from a backward induction procedure that:

Definition 1 (O'Donoghue & Rabin (1999), Definition 4) In a perception-perfect strategy, $s_t = Y, t \in \{0, ..., T\}$ if and only if $U_t(t) \geq U_t(\tau)$, where $\tau = \arg\min_{\iota > t}\{s_\iota = Y\}$ with the exception that $\tau = T + 1$ if $s_\iota = N$ for all $\iota > t$.

This definition means that an individual makes a purchase if and only if the intertemporal utility of doing so is no less than that of delaying it into a future period τ or canceling the demand eventually. With this definition, we now present the main result. In this study, "increasing" means "nondecreasing" and "decreasing" means "nonincreasing." The notation $\lceil \cdot \rceil$ denotes the function that rounds its argument up to the nearest integer.

Theorem 1 (Threshold Perception-Perfect Strategy)

(*i*) *If* $u_t < 0$ *for all* t, *then* $s_t = N$ *for all* t.

(*ii*) *If* $u_t \geq 0$ *for some* t *and* $b > 0$, *then there exists a threshold* κ *such that, for* $t \in \{0, 1, ..., T\}$,

$$s_t = \begin{cases} N & \text{if } t < \kappa, \\ Y & \text{otherwise,} \end{cases}$$

in which $\kappa = \lceil \beta/(1-\beta) - a/b \rceil$.

(*iii*) *If* $u_t \geq 0$ *for some t and* $b \leq 0$, *then* $s_0 = Y$.

Proof By (1) and (2), for $t = 0, ..., T-1$, the individual's intertemporal utility is:

$$U_t(\tau) = \begin{cases} a + bt & \text{if } \tau = t, \\ \beta(a + b\tau) & \text{if } t < \tau \leq T. \end{cases}$$

Let $\Delta U_t(\tau) = U_t(t) - U_t(\tau) = (a + bt) - \beta(a + b\tau) = (1-\beta)a + (1-\beta)bt - \beta b(\tau - t)$, then

$$s_t = \begin{cases} Y & \text{if } \Delta U_t(\tau) \geq 0, \\ N & \text{otherwise.} \end{cases}$$

We consider four cases according to the signs of a and b:

Case 1. $a \geq 0$ and $b \geq 0$. In this case, $s_T = Y$ since $u_T = a + bT \geq 0$ and $u_{T+1} = 0$. Thus, the individual does not cancel the demand, but may delay it. We next show that the individual adopts a threshold strategy. If $s_t = Y$ for all t then the strategy is a threshold strategy with the threshold $\kappa = 0$. If there exists some period t such that $s_t = N$, then let $\iota = \arg\max_t \{s_t = N\}$. If $\iota = 0$, then the strategy is again a threshold strategy with $\kappa = 1$. If $\iota > 0$, then by contradiction, assume that there exists some $t < \iota$ such that $s_t = Y$. Let $\xi = \arg\max_{t<\iota} \{s_t = Y\}$. Thus, $s_\xi = Y$, $s_t = N$ for $t = \xi + 1, \xi + 2, ..., \iota$, and $s_{\iota+1} = Y$. In period ι, that $s_\iota = N$ and $s_{\iota+1} = Y$ implies

$$\Delta U_\iota(\iota + 1) = (1-\beta)a + (1-\beta)b\iota - \beta b < 0.$$

In period ξ, that $s_\xi = Y$, $s_t = N$ for $t = \xi + 1, \xi + 2, ..., \iota$, and $s_{\iota+1} = Y$ implies

$$\Delta U_\xi(\iota + 1) = (1-\beta)a + (1-\beta)b\xi - \beta b(\iota + 1 - \xi) \geq 0.$$

However, these inequalities cannot happen at the same time when $b > 0$ and $\xi < \iota$, leading to a contradiction. Thus, the threshold policy holds.

By the threshold policy, $\kappa = \arg\min_t \{\Delta U_t(t+1) \geq 0, t = 0, ..., T\}$, i.e., κ is the first period such that $U_t(t) \geq U_t(t+1)$; any period $t > \kappa$ must satisfy $U_t(t) \geq U_t(t+1)$ since $s_t = Y$ for all $t > \kappa$ by the threshold policy. Since $t = \beta/(1-\beta) - a/b$ solves $\Delta U_t(t+1) = 0$, straightforwardly,

$$\kappa = \lceil \beta/(1-\beta) - a/b \rceil.$$

Case 2. $a < 0$ and $b \geq 0$. In this case, if $u_t = a + bt < 0$ for all t, then clearly $s_t = N$ for all t. If $u_t = a + bt \geq 0$ for some t, then let T_0 solves $a + bt = 0$ (i.e., $T_0 = -a/b$) and it must be that $u_t \geq 0$ for $t \in [\lceil T_0 \rceil, T]$ and $s_t = N$ for $t \in [0, \lceil T_0 \rceil)$. Now for $t \in [\lceil T_0 \rceil, T]$,

$$u_t = a + bt = (a + b\lceil T_0 \rceil) + b(t - \lceil T_0 \rceil).$$

Let $\tilde{a} = a + b\lceil T_0 \rceil \geq 0$, $\tilde{b} = b$, $\tilde{t} = t - \lceil T_0 \rceil$, and $\tilde{T} = T - \lceil T_0 \rceil$, then Case 1 applies to the transformed problem with $\tilde{a}, \tilde{b}, \tilde{t}$ on $[0, \tilde{T}]$. Thus, the threshold policy holds and the threshold

$$\kappa = \lceil T_0 \rceil + \lceil \beta/(1-\beta) - (a + b\lceil T_0 \rceil)/b \rceil = \lceil \beta/(1-\beta) - a/b \rceil,$$

where $\lceil T_0 \rceil$ is the starting period of the transformed time horizon with respect to $\tilde{t}$, and $\lceil \beta/(1-\beta) - (a + b\lceil T_0 \rceil)/b \rceil$ is the threshold on the transformed time horizon, which is obtained from the expression of κ in Case 1 with $\tilde{a} = a + b\lceil T_0 \rceil \geq 0$ and $\tilde{b} = b$. In fact, this threshold has the same expression as that in Case 1.

Case 3. $a \geq 0$ and $b < 0$. In this case, $u_0 = a \geq 0$. If $u_t < 0$ for all $t > 0$, then clearly $s_0 = Y$ and $s_t = N$ for all $t > 0$. If $u_\tau \geq 0$ for some period $\tau > 0$, then we need to consider whether or not in period 0, the individual will delay the demand to period τ. We note that $\Delta U_0(\tau) = (1-\beta)a - \beta b\tau \geq 0$, so $s_0 = Y$.

Case 4. $a < 0$ and $b < 0$. In this case, $u_t < 0$ for all t, so $s_t = N$ for all t.

The appendix provides a visualization of these cases to illustrate the intuition behind the analysis. Upon analyzing these cases, we further combine the results for a conciser expression. The results in Case 2 when $u_t < 0$ for all t and Case 4 can be combined as (i) in this theorem. The results in Case 1 and Case 2 when $u_t \geq 0$ for some t can be combined as (ii). The result in Case 3 corresponds to (iii). $\square$

This theorem means that an individual makes a purchase after a certain threshold of time. The threshold can be at the beginning of the time horizon, meaning that the individual makes an immediate purchase, or at the end of the time horizon, meaning that the individual cancels the purchase. In terms of structures, this strategy is similar to the stopping rule in studies like Su (2007). In this theorem, Scenario (i) may happen when the good or service to be purchased is not that necessary in comparison with the high cost, so that it is not worthwhile to make the purchase. Scenario (ii) may occur when it is necessary for the individual to purchase the good or service and the individual is overall optimistic about future market conditions. In this case, the individual may delay the purchase. Scenario (iii) may occur when it is necessary for the individual to purchase the good or service, but the individual is overall pessimistic about future market conditions, so the individual chooses to acquire the good or service right at the beginning of the time horizon.

3 Observations and analysis

In the previous section, we develop a behavioral model for expectation-based purchase decisions. In this section, we show that the model can explain real consumer purchase observations. To this end, we carefully select an area: medical service consumption during the COVID-19 pandemic.[1] This area has relatively low confounding effects, because unlike other goods or services which often have many available brands, colors, styles, etc. for consumers to choose, medical services are used to treat certain diseases unchoosable by consumers. In addition, medical services are usually not subject to price shopping (i.e., consumers usually do not compare prices among different stores before purchasing), demand sensitivity to price (medical service prices are highly regulated and stable, and patients' demand for medically necessary services usually does not significantly change with price), and supply chain issues. Thus, with less confounding factors than other areas, medical service data render a neat way to derive sharp insights.

We collect medical service data that contain the following key pieces of information: what types of consumers (consumer demographics) acquired what kinds of medical services (medical service categories) at what locations and what times (medical visit records). We collect medical visit records from SafeGraph, a high-quality database that provides accurate and comprehensive foot traffic data from census block groups (CBGs) to business establishments by tracking mobile devices in the entire USA SafeGraph (2021). A CBG is the smallest geographical unit used by the U.S. Census Bureau to publish sample data. As household-level data are confidential, the anonymized CBG data serve as the basic units. From SafeGraph, we collect weekly visit data from all the 6125 CBGs in North Carolina to 16,325 healthcare facilities (HFs, e.g., clinics and hospitals) for the first 37 weeks of 2020. This time period is selected around the stay-at-home lockdown to allow sharp behavioral observations.[2] The appendix contains more details about the data collection and exploration process in this section.

Upon obtaining the CBG-to-HF traffic data, we further obtain consumer demographic data (per capita income, health insurance status, etc.) of the CBGs and service categories (immunology, cardiology, neurology, etc.) of the HFs. We obtain the demographic data by accessing the American Community Survey (2016) organized by SafeGraph, with 20 (0.3% of) CBGs dropped due to the lack of data. The identification of the HFs' service categories is more challenging, since the SafeGraph data do not provide such information. We accomplish this by first matching the HFs to Yelp businesses through business locations, and then acquiring the Yelp business category tags (Yelp 2021c) of the matched HFs. After that, we associate the Yelp business category tags with standard medical categories according to the medical specialty guide of the Association of American Medical Colleges AAMC (2021) and the American Medical Association AMA (2021). This classifies 14,655 (89.8%

[1] This study considers medical services in all specialties (e.g., immunology, cardiology, dentistry, neurology, optometry, pediatrics, and urology), not just those related to the coronavirus.

[2] World Health Organization (WHO) declared the COVID-19 outbreak a global pandemic on March 11, 2020. Starting on March 15, US states issued formal stay-at-home, shelter-in-place, or similar lockdown orders, which, among other requirements, specifically required residents to remain home at all times, unless engaging in essential activities Mendelson (2020). As of May 20, 2020, all states started to lift their stay-at-home orders and other restrictions on businesses Mendelson (2020). We focus on the consumption data before, during and after the lockdown because the lockdown had the most dramatic restrictions on people's activities and thus the data around the lockdown are expected to exhibit clear behavioral patterns.

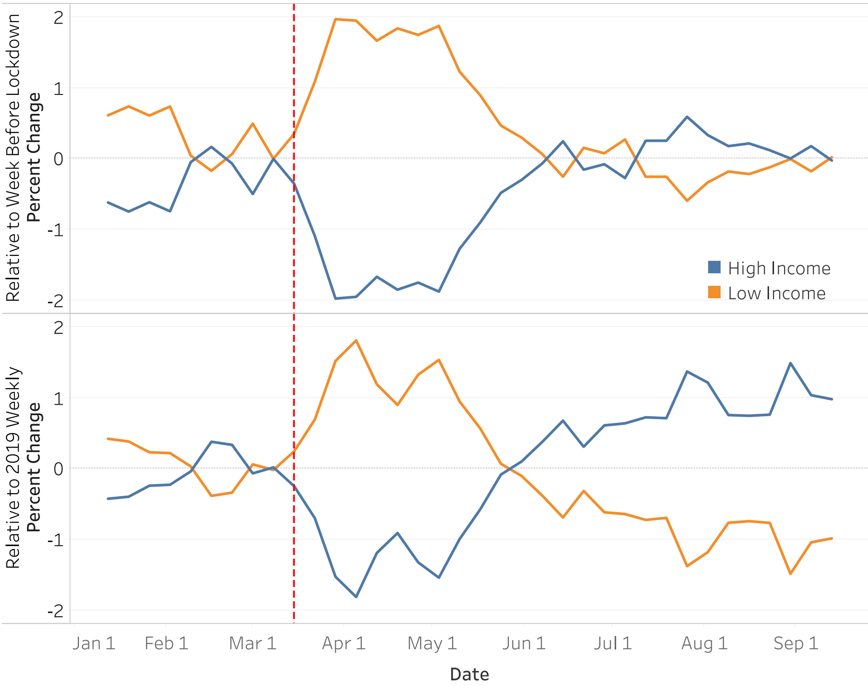

Fig. 1 Relative Medical Visit Change of Different Household Income Levels

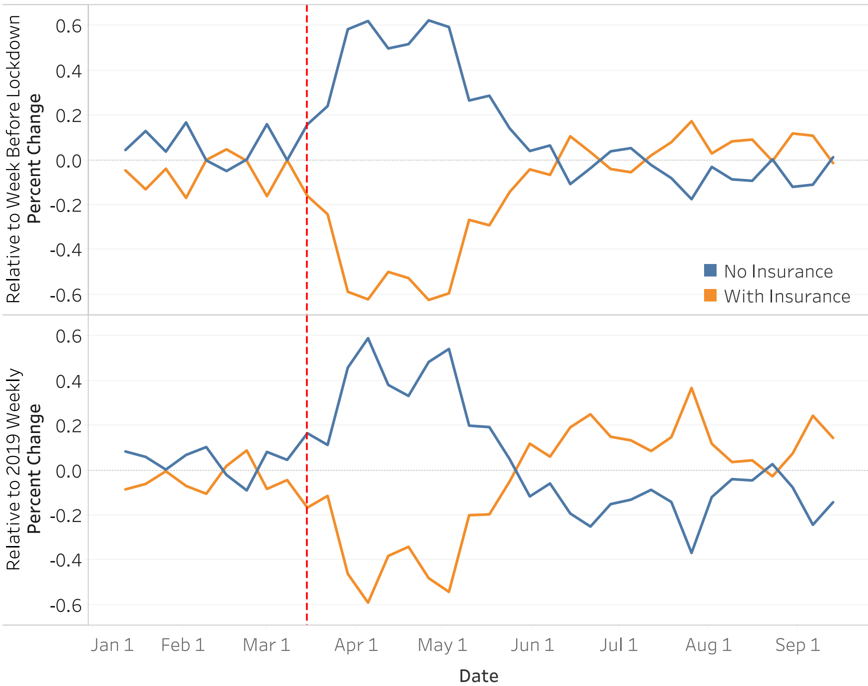

Fig. 2 Relative Medical Visit Change of Different Insurance Status

of) HFs into 39 categories, with the remaining HFs that do not have matched categories dropped.

An exploration of the data reveals interesting findings. While the pandemic has adversely affected medical service consumption of all individuals, the impacts on individuals with different income levels and insurance status are very different, as shown in Figs. 1 and 2. In the figures, the horizontal axes represent time and the vertical dashed line indicates the lockdown start date due to the pandemic. To control for factors such as trend and seasonality, the vertical axes report the weekly visit percentage change *relative to* the week right before the lockdown (top panel) and *relative to* each corresponding week in 2019 (bottom panel), respectively. For example, if the percentage of low-income individuals in a week is 52% and that in the corresponding benchmark week is 50%, then a percentage change of 2% is reported in the figures.[3] The low- and high-income groups are divided at the median household income level (roughly $60,000).[4] The figures clearly show a change in the composition of individuals who sought medical services. Specifically, right after the beginning of the lockdown, individuals with high incomes or with insurance exhibited a decreasing portion of the medical visits, whereas individuals with low incomes or without insurance gained an increasing portion. This consumer *group composition change* is statistically significant (i.e., it is not simply due to randomness), as detailed in the appendix, and, to our best knowledge, such change patterns have not been discovered by any prior studies.

What drove this group composition change? We next show that our expectation-based behavior model can provide a sound explanation. In medical service consumption during the pandemic, three factors play key roles. First, the *value of service* is an intrinsic feature of the service sought. If the service sought is not that medically necessary (e.g., treating a mild, self-healing disease), then an individual, in view of infection risks, may cancel the visit. While this value of service factor is important, it is unlikely to be the main cause for the observed heterogeneous patterns because each income or insurance group is likely affected by this factor in similar ways (the compositions of services sought by each group are in fact consistent over time, as shown later). Second, *health cautiousness* is another important factor, as different groups of consumers may have varying degrees of cautiousness toward infection risks, leading to heterogeneous decisions. Finally, the pandemic has also had disparate impacts on people's financial conditions: studies have shown that low-wage workers experienced more and longer job losses Cajner et al. (2020); Chetty et al. (2020); Gonzalez et al. (2020). Thus, *financial instability concern* is another critical factor that may cause the heterogeneous decisions.

Therefore, the interplay of *health cautiousness* and *financial instability concern* is likely to be the main cause for the observed heterogeneity. An individual with a

[3] The two curves in each plot are symmetric with respect to the horizontal axis, because, as an example, a 2% increase in high-income visitors implies a 2% decrease in low-income visitors; the percentages of the different groups of visitors add up to one.

[4] We also explore dividing data in other ways (e.g., by mean household income level) and find that the empirical patterns are not sensitive to the selection of the cutoff point.

low income or without insurance is likely to be more concerned about their financial instability and the relative affordability of the service in the future. Hence, that individual tends to have a large, positive b_c and, consequently, a negative b (recall that $b = b_r - b_c$). The individual then makes an early purchase according to our theorem. In contrast, an individual with a high income or with insurance is likely to be less concerned about their financial status. If, in addition, the individual is concerned about the current health risk and expects the risk will be lower in the future, then $b_c < 0$ and $b > 0$ and the individual delays the purchase. In our observations, each group (each curve in Figs. 1 and 2) is likely to contain a heterogeneity of individuals with different expectations. However, by the above analysis, the high-income or insured groups are likely to contain more individuals who tend to more significantly delay their purchases. Thus, the observation can be explained by our expectation-based behavioral model.

While we have shown that our model can explain the observation, we also explore some other plausible explanations and show that they in fact cannot explain the observation. First, a natural intuition for the composition change might be that certain groups of people face a high risk of exposure to the coronavirus and, hence, must seek immediate medical services. For example, many low-income individuals are essential workers with higher infection risks, so the increasing portion of their medical visits might be attributed to *virus-induced* medical visits. While this might sound reasonable, the medical visit data in this study include all medical specialties (e.g., immunology, cardiology, dentistry, neurology, optometry, pediatrics, and urology), and visits directly caused by the coronavirus only represent a very small portion. Thus, virus-induced medical visits are unlikely to cause the composition change.

Another possible explanation might be that the pandemic altered the categories of medical services sought by the different groups of people, so that they needed to see doctors for different types of diseases with different degrees of urgency. To see whether or not this explanation holds, we perform a statistical analysis on the service category change over time (details in the appendix). The result shows that the service category compositions are consistent over time, i.e., the different groups of people saw doctors for statistically the same compositions of medical services as before. This matches our intuition since the coronavirus is unlikely to significantly change people's general medical needs in the wide variety of categories (immunology, cardiology, dentistry, etc.). In summary, virus-induced visits and service category changes cannot explain the observation.

4 Extensions

In our analysis so far, we have developed a behavioral model and showed that the model can explain real observations. While we believe the model captures major elements in expectation-based purchase decision-making, we have made simplifying assumptions. One major assumption is that, in the (β, δ) quasi hyperbolic discounting formulation, we have assumed that the time-consistent discount parameter $\delta = 1$ for simplicity. We next extend our analysis to the case with $\delta < 1$ to generalize our results and insights. When $\delta \le 1$ (this analysis includes the original $\delta = 1$ case as a special case), the intertemporal utility function (1) becomes

$$U_t(\tau) = \begin{cases} \delta^t u_t & \text{if } \tau = t, \\ \beta\delta^\tau u_\tau & \text{if } \tau > t. \end{cases}$$

Note that here, a strategically equivalent expression is

$$U_t(\tau) = \begin{cases} u_t & \text{if } \tau = t, \\ \beta\delta^{\tau-t} u_\tau & \text{if } \tau > t. \end{cases}$$

The two expressions only differ in that the former uses the discounted utility at time 0, while the latter uses the discounted utility at time t. However, the two expressions yield exactly the same strategy. We thus adopt the former expression.

To analyze this general case with $\delta \le 1$, we let $v_t = \delta^t u_t = \delta^t(a + bt)$. The intertemporal utility then becomes

$$U_t(\tau) = \begin{cases} v_t & \text{if } \tau = t, \\ \beta v_\tau & \text{if } \tau > t. \end{cases} \tag{3}$$

This utility function has the same format as the original utility function (1), but unlike $u_t = a + bt$ in (1), $v_t = \delta^t(a + bt)$ here is neither linear nor even monotonic. In fact, it can be shown that (details in appendix), depending on the sign of b, v_t is either unimodal or U-shaped. At first glance, this change of the expectation form would alter the threshold strategy structure. This is, however, not the case, as shown in the following theorem for general quasi hyperbolic discounting (i.e., $0 \le \beta \le 1, 0 \le \delta \le 1$). The proof of this theorem, as well as that of Theorem 3, is relegated to the appendix.

Theorem 2 (Threshold Perception-Perfect Strategy With $0 \le \beta \le 1, 0 \le \delta \le 1$)

(*i*) *If* $u_t < 0$ *for all* t, *then* $s_t = N$ *for all* t.

(*ii*) *If* $u_t \ge 0$ *for some* t *and* $b > 0$, *then there exists a threshold* κ *such that*, *for* $t \in \{0, 1, ..., T\}$,

$$s_t = \begin{cases} N & \text{if } t < \kappa, \\ Y & \text{otherwise.} \end{cases}$$

(*iii*) *If* $u_t \ge 0$ *for some* t *and* $b \le 0$, *then* $s_0 = Y$.

The strategy in Theorem 2 is the same as that in Theorem 1, except that the expression of the threshold κ in (ii) is much more complicated and hence is given in the appendix. Theorem 2 shows that the threshold perception-perfect strategy continues to hold for general quasi hyperbolic discounting. For example, the strategy holds in the special case of $\beta = 1$, which corresponds to the classical geometric discounting scheme. Thus, the insights we have derived are robust with respect to the discounting scheme—the strategy structure and behavioral heterogeneity apply to general expectation-based purchase decisions, regardless of the specific discounting scheme.

In fact, while Theorem 2 generalizes the analysis to general quasi hyperbolic discounting which features unimodal or U-shaped expectations, we can further generalize the analysis to any expectation forms. Consider the intertemporal utility in (3) but v_t now can take any general form. We can conduct the analysis by dividing the expectation function into monotonic pieces and examining the strategy on each monotonic piece in a backward manner according to the following theorem.

Theorem 3 (Generalized Threshold Perception-Perfect Strategy)

(i) $s_t = Y$ *only if* $v_t \geq 0$.

(ii) If v_t *is increasing on* $[t_1, t_2]$, *then that* $s_\iota = Y$ *for some* $\iota \in [t_1, t_2]$ *implies that* $s_t = Y$ *for all* $t \in [\iota, t_2]$.

(iii) If v_t *is decreasing on* $[t_1, t_2]$, *then that* $s_\iota = Y$ *for some* $\iota \in [t_1, t_2]$ *implies that* $s_t = Y$ *for all* $t \in [t_1, \iota]$.

Theorem 3 states that when v_t is increasing on an interval, the strategy may switch from N's to Y's; when u_t is decreasing on an interval, the strategy may switch from Y's to N's. Thus, *local monotonicity drives the threshold strategy structure*. As any function can be divided into monotonic pieces, Theorem 3 greatly facilitates the analysis of purchase decisions under general expectations.

5 Ending remarks

In this study, we develop a general behavior model to capture consumers' purchase decisions based on expectations of market conditions. The model features a multiple-selves formulation and incorporates consumers' present-biased and time-consistent preferences. An analysis based on the model shows that a consumer adopts a threshold perception-perfect strategy when making a purchase decision, i.e., a consumer purchases a good or service after a certain threshold of time. Consumers who are overall pessimistic about future market conditions make an immediate purchase, whereas consumers who are overall optimistic about future conditions may delay the purchase.

To illustrate whether the model can explain real observations, we compile a novel dataset on medical service consumption during the COVID-19 pandemic. The data indicate that the pandemic lockdown more significantly delayed the medical service consumption of individuals with high incomes or with health insurance. This observation can be explained by our model where individuals form expectations on health risks and financial instability. Under the influence of the expectations, the high-income and insured groups are likely to contain more individuals who tend to delay their purchases, thus explaining the observed heterogeneity.

It is worth noting that although our analysis uses COVID-19 pandemic data, the purpose is not to examine the pandemic's impact. Instead, we select the data because the pandemic significantly affects consumers' expectations, enabling sharp insights. In addition, the purpose of our data exploration is not to establish causality, but to demonstrate that our model can well explain real observations. In fact, our model can also be used to explain other phenomena. We provide several examples next. First, consumers often aggressively stockpile or hoard necessities (preservable food, toilet paper, etc.) during crises (see, e.g., Corkery et al. 2020). Prior literature has explained this behavior by a herding effect (consumers simply follow others' action to stockpile necessities; e.g., Baddeley 2020). However, the herding effect cannot explain why "others" take the action in the first place. Our model can provide an explanation: when a crisis occurs, consumers naturally have a very pessimistic view of the future affordability and availability of the necessities (i.e., a very negative b in the model) and hence make immediate purchases. As another example, North Carolina shoppers often raid grocery shelves right after seeing a snow forecast. Chris (2018) reported such an event for a less than one inch of snow. The explanation is that the less-than-one-inch snow, though unlikely to cause any real supply disruptions, was often perceived as a major weather event since significant snow is uncommon in many areas of North Carolina. Thus, the expectation drove shoppers to make the purchases. Yet another example regards the sharply declined service consumption after the September 11 terrorist attacks (e.g., a more than 20% decrease in the transportation service passenger index according to BTS (2017)). This may result from the perceived safety risks right after the attacks and relatively optimistic views about future conditions (i.e., a positive b in the model).

We conclude this study by discussing some of its limitations and possible future research directions. First, while our study focuses on deriving analytical insights into expectation-based purchase behavior, our model can be used for empirical analysis. For example, an empirical study that uses the medical service visits data to estimate model parameters and understand consumers' expectations in medical service consumption would be an interesting direction to pursue. Second, while our study makes observations in the medical service context, examining consumers' purchase decisions in other areas would enrich the insights. Third, a weakness in our data exploration is the lack of individual-level or household-level data (such data are confidential). For example, in characterizing the low-income group, the household income data of census block groups, instead of individual household income data, are used. In the future, if data with finer granularity become available, then the observations can be further refined.

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Declarations

This research does not involve human participants and/or animals.

Ethics approval Not applicable

Informed consent Not applicable

Conflict of interest The authors declare no competing interests.

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