A More Experimental Details

This appendix section presents the robustness findings along with additional details on the simulation parameters used.

A.1 Robustness

As mentioned in §5.2, we have included the robustness plot here as well to provide a more detailed analysis. That is, to check for robustness, we run the same original experiment mentioned in §5.2, as follows:

The experiment is conducted using the original set of parameters in §5.1, ensuring consistency across all trials. To account for variability and assess robustness, the model is executed for 20 different randomly generated seeds. The resulting Figure 5 provides a visualization of the data by displaying the mean value, as well as error bars are included to depict the 95% confidence interval, offering insight into the robustness of the patterns shown before.

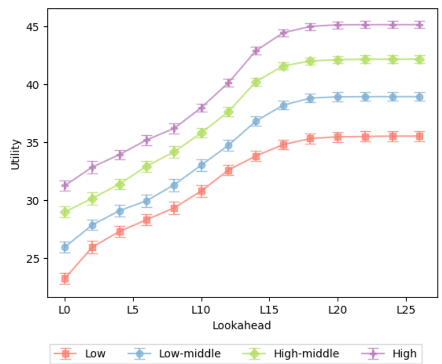


Figure 5: The simulation in 5.2 is carried out with the original parameters in 5.1. Results are for running the simulation for 20 different randomly generated seeds. The plot displays the mean value, and the error bars display a 95% confidence interval.

Analysis. The insights from Figure 5 are similar to the ones in §5.2:

- The results and consumption patterns observed before are observed in this plot, which indicates robustness.
- Workers with limited foresight and minimal knowledge of future schedule instability experience notably lower financial utility than those with greater lookahead.
- Overall, lookahead has a positive effect: workers with more foresight can better navigate financial decisions, leading to higher utility.
- Full knowledge of work schedules in advance is not necessary. Even beyond the midpoint threshold (lookahead 17), workers achieve a utility level comparable to those with complete schedule information.
- Higher income directly translates to greater utility, as individuals can consume without financial constraints. This is clearly reflected in the consistent upward shift of the plots along the y-axis.

A.2 More Clarifications on Simulation Parameters Used in §5.1

Why IQR and IQR Setting. To ensure a representative and analytically robust income distribution, we remove extreme low and high income outliers using the Interquartile Range (IQR) method. Income data is characteristically right-skewed (Benhabib & Bisin, 2018), with a small number of individuals earning disproportionately high incomes. The IQR method is particularly well-suited for such data because it is non-parametric and does not assume a normal distribution, unlike z-score-based methods, which can be distorted by skewness (Insights, 2025; Hubert & Van der Veeken, 2008; Whaley III, 2005). Specifically, per IQR's definition, the outliers are values below ($Q1 - 1.5 \times \text{IQR}$) or above ($Q3 + 1.5 \times \text{IQR}$) where $\text{IQR} = Q3 - Q1$, effectively trimming only the extreme tails while preserving the integrity of the central distribution.

Shocks. The parameters chosen for modeling income shocks are grounded in empirical findings from real-world data. Since the shocks are very different household by household and occupation by occupation, the common practice in economics is to adopt a reasonable range.

According to the JPMorgan Chase Institute, income volatility remained fairly stable between 2013 and 2018, with households at the median experiencing a 36% change in income from month to month on average (JPMorgan Chase Institute, 2016) (an additional set of experiments based on this shock profile is in §B.5). However, volatility levels vary substantially by household and occupation. The same report notes that income variability is highly heterogeneous, both across different families and over time for the same family. The median standard deviation of volatility is reported as 0.37.

Further illustrating this variability, retail workers often face unstable schedules that result in up to a 50% variation in work hours (and the corresponding earnings) during certain months (CLASP, 2022). Similarly, gig workers such as rideshare and delivery drivers experience changes in earnings tied to fluctuating hours and platform demand, with income shifts ranging from 3.4% to roughly 14% month-over-month depending on market conditions and app algorithms (Insider, 2024).

Taking these observations into account and to have a reasonable shock profile, we opt for income shocks that ranges from -0.4 to 0.4, with shocks occurring as $(1 + r) \times \text{income}$, where r represents the shock value. The shocks are generated from a Bernoulli process, with the shock size parameter r uniformly sampled from $[-0.4, 0.4]$.

Discounting Factor β. Similarly, the common practice in economics is to adopt a standard, reasonable value for the discount factor, typically set at 0.95. This practice is widespread in the literature and has been employed in numerous studies (Patnaik et al., 2022; Cooper & Willis, 2014)[6]. However, a body of research seeks to go beyond this uniform assumption by estimating more context-sensitive β values that vary across demographic groups. For example, as discussed in the following Sections B.1, B.2, and B.3, β can change with education level or employment status. We provide a detailed analysis of these more granular real-world scenarios in Appendix B.

Return Rates. The return rate ranges used in §5.1 are grounded in empirical observations of *typical* historical asset performance of 5 years preceding 2020 across a broad spectrum (Carlson, 2021; Bank, 2020). As with most economic parameters, return rates can vary significantly depending on individual circumstances and the type of asset involved. We consider typical asset returns, not highly-volatile assets. For instance, if an individual owns cryptocurrency and other very high-risk assets, they can have return rates like +215.07% or +539.96% during certain quarters and then experience very drastic drops in asset values [7].

Therefore, like other parameters, the common practice is to choose a range that reflects realistic variability. However, as further examined in §B.4, a more granular analysis is possible by focusing on specific typical asset classes (such as stocks or cash), which allows for a more precise assessment of return dynamics. Still, these specific return rates generally remain within the broader range defined in the initial simulation.

The description of a range and the added variance of to returns implies return rates uniformly distributed in a given range. With probability 0.1, we get an additive shock to the return rates where the additive amount is sampled from a different uniform distribution (Thus, *'a range and the added variance'* is not about uniform + Normal additive returns).

[6] `https://behaviouraleconomics.jasoncollins.blog/intertemporal-choice/present-bias-examples`
[7] `https://www.coinglass.com/today`

Discretization of the Dynamic Programming. In the simulations, the asset space is discretized into integral buckets with the gap between the buckets set to 1 where the number of buckets depends on the difference between highest attainable assets and the lowest possible assets (which could be non-zero depending on the income distribution).

Details of the Simulation Runs. The main results presented in §5.2 are based on a single set of simulation runs for representative individuals within each income group and for 50 runs in the mitigation experiments. This choice was intentional, as our goal was to avoid averaging across agents, which can obscure meaningful behavioral variation, especially in a setting where individual-level dynamics are of interest. As discussed in the main text, the qualitative trends in consumption and utility remain consistent across different random seeds and repeated runs. *However, to meaningfully support this, we include robustness additional results across 20 random seeds in Figures 5 and 2, which confirm the stability of the main patterns.*

In this context, the empirical findings serve as a complement to the theoretical results established earlier, helping to illustrate broader behavioral patterns rather than focusing on fine-grained empirical fluctuations. Given the heterogeneity of agents in real-world socioeconomic environments, as shown in the detailed parameter justifications above, our interest lies in capturing these general dynamics.

B More Real-world Problems

In this appendix, we explore additional scenarios informed by real-world data and observed phenomena.

B.1 Patience Factor based on β

In models of intertemporal choice, the parameter β denotes the *subjective discount factor*, capturing the extent to which individuals prefer present consumption over future consumption. A β value between 0 and 1 indicates that future consumption is valued less than immediate consumption, with lower values reflecting a stronger preference for the present. This formulation is closely aligned with the concept of *present bias*, which describes the tendency to overvalue immediate rewards relative to delayed ones.

A lower β implies greater impatience, signifying that individuals are more inclined to choose smaller, immediate rewards over larger, delayed alternatives. In contrast, higher values of β are associated with patience and a stronger orientation toward future utility.

Empirical studies on real-world events have documented that there are economic agents who exhibit more *present-focused preferences*, meaning they are more prone to choose actions that yield immediate utility when those actions affect the present, compared to when all consequences are shifted into the future (Ericson & Laibson, 2019; Lockwood, 2020). In essence, these individuals make more impulsive decisions in the short term than they would if facing the same set of outcomes at a future point in time.

The value of β plays a critical role in determining financial behaviors such as saving and borrowing. More impatient individuals (with lower β) are typically more susceptible to accumulating debt, while those with higher β are more likely to delay gratification and engage in future-oriented behaviors like saving. In the following examples based on real-world problems, we explore how these dynamics unfold in different contexts.

B.2 Unemployment

This section examines one of the most prevalent real-world problems: job insecurity and unemployment. We focus on how unemployed individuals experience varying levels of utility based on their capacity for *lookahead*, that is, their ability to anticipate future events. Specifically, the analysis compares unemployed agents who have minimal or no information about the future against those with greater foresight (and the related β).

Although this paper primarily addresses dynamic work scheduling, the underlying framework also applies directly to unemployed individuals, who typically face profound uncertainty. An unemployed person may not know: When or whether they will find a job, whether any job obtained will be full-time or part-time, how long unemployment insurance (UI) benefits will last, whether they will experience unanticipated financial shocks during the job search, how partial employment affects UI eligibility and payments, and how and when to report earnings to maintain compliance with UI regulations.

Unemployment Insurance (UI) provides temporary income to eligible workers who lose their jobs through no fault of their own. However, *UI exhaustion* occurs once an individual has received all the benefits for which they are eligible in a given benefit year. At that point, no further payments are made unless the claim is renewed or the individual qualifies for extended benefits (Institution, 2020; on Budget & Priorities, 2021).

The actual duration of UI varies significantly by individual and state, influenced by the following factors: UI is typically calculated as a percentage of previous wages, and individuals with higher earnings get paid more. Also, most U.S. states allow up to 26 weeks of standard UI benefits. However, during economic downturns or recessions, extended benefits may become available (on Budget & Priorities, 2021).

Importantly, UI benefits generally cease when an individual finds full-time employment. For part-time employment, the rules are more nuanced. If the individual remains underemployed and continues to meet the eligibility requirements (typically related to earnings thresholds), they may still receive partial benefits. However, there is uncertainty on what can be categorized as an eligible partial employment and even if they are still eligible, UI payments may be proportionally reduced based on the income earned (Inc., 2021).

This complexity creates an environment where individuals make critical consumption and job search decisions under uncertainty. Prior work by (Lockwood, 2020; Ganong & Noel, 2019) provides empirical evidence on consumption behavior during unemployment, revealing that the majority (approximately 75%) of unemployed households exhibit a discount factor $\beta = 0.9$ which indicates more patience.

Thus, to explore this example, for our simulations, we use $\beta = 0.9$, following their setup. All other simulation parameters are similar to §5.1.

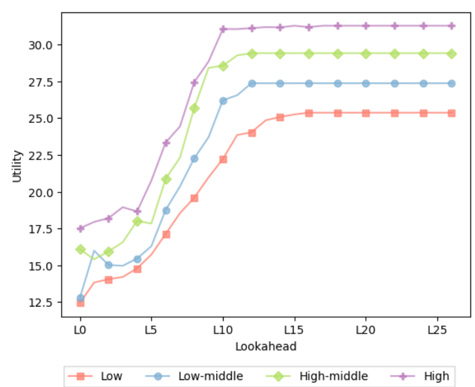


Figure 6: The final utility gained for different levels of lookahead is illustrated for the four classes, each comprising 27 unemployed individuals. Agents are of similar features, with variations solely based on the temporal aspect, i.e., the amount of lookahead in their future schedules. The x-axis depicts the lookahead value and the y-axis represents the total utility at the end of T steps. Since agents are unemployed, we set β to be 0.9 based on the prior research (Lockwood, 2020; Ganong & Noel, 2019).

Analysis Figure 6 illustrates the impact of foresight on utility for unemployed individuals across income levels. Three main insights emerge:

1. Individuals with little to no information about the future face significant utility losses. This is expected, as uncertainty in income, benefit eligibility, and job prospects limits their ability to plan and allocate resources effectively.

2. With increased foresight, individuals make better-informed financial decisions. The utility gain with more lookahead demonstrates that even in uncertain environments, information helps optimize consumption and savings strategies.

3. Higher-earning individuals consistently achieve greater utility, which aligns with their ability to consume without constraint. This result is evident from the upward shift in utility across the y-axis for the higher-earning group.

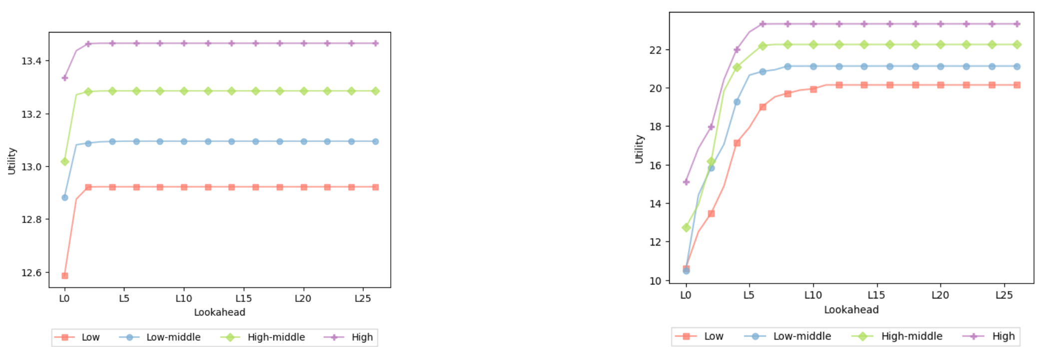
B.3 Real-world Educational-based Patience Factors

In this section, we examine another real-world scenario: the relationship between educational attainment, consumption behavior, and the benefits of having lookahead. While the previously used discount factor of $\beta = 0.95$ in §5.1 represents a standard and commonly accepted value, our earlier analysis on unemployment illustrates that patience can vary across different demographic groups. This motivates a more context-sensitive exploration of β, particularly as it relates to educational background.

Prior empirical research demonstrates that individuals' time preferences reflected in their β values are systematically associated with their level of education. Specifically, individuals with a high school diploma but no college degree tend to exhibit more impatient behavior, corresponding to a lower β of approximately 0.50.

Conversely, those with a college degree tend to be more patient, with an estimated β of 0.83 (Laibson et al., 2024; Lockwood, 2020). Therefore, in this simulation, we adopt $\beta = 0.50$ for workers with mid-level education and $\beta = 0.83$ for those with higher education, to better align our model with observed real-world behavior.

Except for this variation in β values based on educational attainment, the experimental setup remains consistent with the baseline configuration described in §5.1. Figure 7 presents the resulting utility outcomes for workers of varying education levels.



(a) High school degree lookahead analysis

(b) College degree lookahead analysis

Figure 7: The final utility gained for different levels of lookahead is illustrated for four income classes, each comprising 27 individuals. Workers are of similar features, with variations solely based on the temporal aspect, i.e., the amount of lookahead in their work schedules. The x-axis depicts the lookahead value, and the y-axis represents the total utility at the end of T steps. Here, in the left plot, the income classes have a high school (i.e., mid-level) education level with $\beta = 0.5$ and they have higher education (i.e., college degree) on the right plot with $\beta = 0.83$.

Analysis. The insights derived from Figure 7 can be summarized through several key observations concerning workers with lower educational attainment:

- Workers with lower education levels tend to exhibit higher levels of impatience. As a result, they reach their peak attainable utility more quickly than their more patient counterparts. For instance, individuals with only a high school education converge to their maximum utility within approximately 5 weeks, whereas college-educated workers continue to gain from lookahead information for up to 10 weeks.
- As observed in earlier settings, limited foresight leads to significantly lower utility. Workers who lack access to future information or are unable to anticipate potential instability in their schedules are less able to optimize their consumption, resulting in diminished financial well-being.

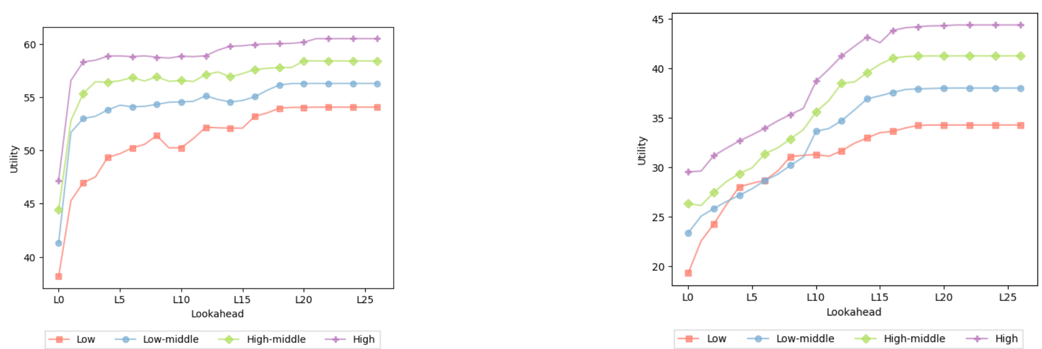
- Greater lookahead consistently improves utility outcomes. The ability to foresee and plan around future events allows workers to adjust their financial decisions accordingly (particularly within the first 5 weeks for high school-educated workers and the first 10 weeks for those with college degrees).
- Higher income levels and higher education predictably lead to higher utility even without lookahead. This is reflected in the difference in the range of the utility values along the y-axis in the two plots.

B.4 Real-world Return Rates on Liquid Assets

Similar to §5.3, this section's goal is to investigate the impact of asset appreciation and depreciation on decision-making across various levels of lookahead, i.e., some workers are already at a (dis)advantage in terms of assets. While the return rates discussed in §5.3 are accurate when considering a broad spectrum of assets and realistic return ranges (Carlson, 2021; Bank, 2020), we can refine this analysis by focusing on specific categories, particularly liquid assets. Liquid assets refer to holdings that can be readily converted into cash with minimal loss in value.

In this section, we examine two of the most commonly held liquid assets: *cash* and *stocks*. The primary distinction between them lies in their nature: stocks are investment vehicles that yield returns over time, whereas cash represents direct monetary holdings. In contrast, cash does not appreciate and is vulnerable to inflationary erosion but represents the most liquid form of asset ownership [8].

To model realistic return variability, we use empirical data from the five years preceding 2020 (i.e., 2016–2020) (Carlson, 2021; Bank, 2020). For stocks, we set a return range of 10%. For cash-only holdings, we assume the individual is holding cash only, so based on real-world returns (Carlson, 2021; Bank, 2020), we use -0.5%. All other experimental conditions are held similar to 5.3.



(a) Stocks return rate analysis

(b) Cash return rate analysis

Figure 8: Individuals with similar features but varying levels of lookahead under various return rates. The return rates are set to 1.1 for stocks in the left plot. In the right plot, the return rates are set to 0.995 for cash. Other simulation parameters remain the same as 5.1.

Analysis. The results, depicted in Figure 8, are consistent with those found in §5.3 and offer several noteworthy insights:

- Individuals achieve higher utility under favorable return conditions, like stocks. This trend underscores the intuitive relationship between asset performance and consumption outcomes.
- When holding a *very mildly* depreciating asset such as cash (only -0.5% depreciation), lookahead still boosts utility. Individuals quickly adapt their consumption in anticipation of diminishing purchasing power. Notably, since this asset is depreciating very mildly, the individuals attain near-maximum utility later than the original negative return setting in §5.3 and by lookahead 15.

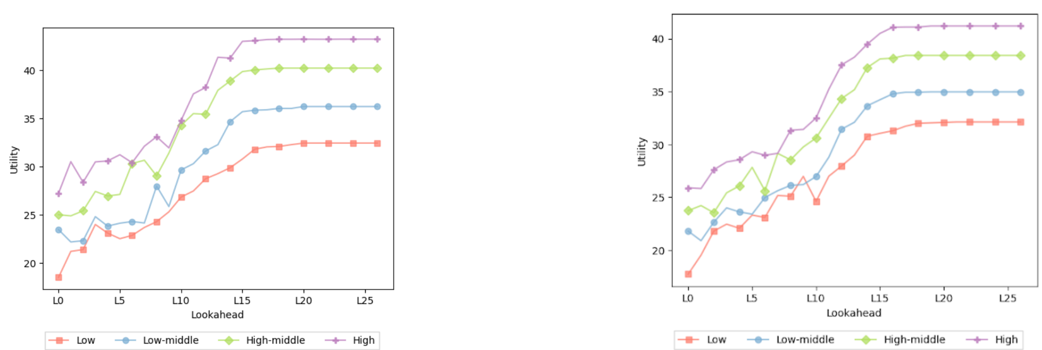
[8]https://www.investopedia.com/articles/investing/103015/cash-vs-bonds-what-pick-times-uncertainty

- In scenarios with anticipated positive returns (e.g., stocks), the knowledge of a 10% increase helps individuals a lot in the beginning. However, after lookahead 5, individuals can afford to delay consumption, knowing they are likely to benefit from capital appreciation. As a result, convergence to peak utility occurs more gradually across all income groups (very late and around lookahead 20 here), reflecting increased consumption flexibility.

B.5 More Real-world Shock Profile Case Studies

In this section, we examine another real-world scenario: the shock profiles based on the statistics provided by JPMorgan Chase Institute (2016). According to the JPMorgan Chase Institute (as explained in §5.1 as well as §A.2), income volatility remained fairly stable between 2013 and 2018, with households at the median experiencing a 36% change in income from month to month on average (JPMorgan Chase Institute, 2016). However, volatility levels vary substantially by household and occupation. The same report notes that the median standard deviation of volatility is 0.37.

Thus, we explore a case in which the shock value is selected uniformly at random from -0.36 to 0.36. We also consider the *standard deviation of volatility* (i.e., coefficient of variation as the ratio of the standard deviation to the mean), which is reported as 0.37. This is done by the coefficient of variation being defined as $\frac{\sigma}{\mu}$ where σ^2 is the variance and μ is the mean. We set the coefficient of variance to 0.37, i.e., $\frac{\sigma}{\mu} = 0.37$, which yields $\sigma = 0.37\mu$. In this case, we have $\mu = -0.36$. We consider the values in the range of $[\mu + 2\sigma, \mu - 2\sigma]$ so we end up with -0.6264 and -0.0936 as the lower and upper bounds of the range from which shocks are uniformly sampled. All other parameters are similar to §5.1.



(a) Shock profile analysis

(b) Shock with standard deviation of volatility analysis

Figure 9: Individuals with similar features but varying levels of lookahead under a new shock profile. Shocks selected uniformly at random from -0.36 to 0.36 (left plot). We also consider the standard deviation of volatility, which is reported as 0.37 (right plot). Shocks are based on the exact statistics in (JPMorgan Chase Institute, 2016). Other simulation parameters remain the same as 5.1.

Analysis. The takeaways from Figure 9 align closely with the findings discussed in §5.2 (since the shock profiles we originally opted for were based on realistic ranges similar to the ones listed in (JPMorgan Chase Institute, 2016)):

- The same trends and consumption behaviors previously observed are present here as well, reinforcing the robustness of our results.
- Individuals with limited foresight and little knowledge about future scheduling uncertainty consistently experience lower financial utility compared to those with longer lookahead horizons.
- Greater lookahead generally leads to improved outcomes: individuals with more foresight are able to make more informed financial decisions, resulting in higher overall utility.
- Having full foresight is not strictly necessary. Once the lookahead horizon reaches around 17 weeks, utility levels closely approach those achieved under full schedule awareness.

- Increases in income correlate directly with higher utility, as they reduce financial constraints on consumption. This is clearly seen in the upward shift of the plots along the y-axis.
- The standard deviation of volatility introduces fluctuations, particularly affecting the two lower-income classes, which are inherently more financially unstable. However, since the reported deviation does not indicate a significant variation, the overall trend remains unchanged.
- The utility range for the deviation plot is of lower values compared to the left plot (since the shock range in the right plot was mostly negative), resulting in an overall lower utility range (as reflected in the values along the y-axis).