CHRONOS AND CODES: AN EXPLORATION OF THE ISSUE OF TIME POVERTY AMONG IT PROFESSIONALS

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Abstract

Time poverty is one of the crucial factors that affect the productivity of IT workers, especially in today's fast-paced work environment. This study aims to explore the concept of time poverty among the IT employees of Cochin and Delhi, via a threefold approach using a primary survey. First, the study quantifies absolute and relative measures of time inadequacy, drawing on frameworks from Vickery (1977) as well as Harvey & Mukhopadhyay (2006). The influence of many socioeconomic and demographic factors on each worker's likelihood of acutely experiencing shortage of time is then investigated by employing logistic regression analysis. Finally, using a contingent valuation methodology (CVM) with multiple bounded iterative bidding, the study estimates the workers' willingness to pay (WTP) towards the Time Value Deduction (TVD) fund, a semi-hypothetical policy designed to provide an additional day off per week. Interval-censored regression models are further utilised to analyse the factors influencing WTP and to cross-examine the trends observed in the logit model. The results show that around 47% of IT workers were classified as absolutely time-poor, while around 29% experienced relative time poverty without being money-poor. Analysis of the logit model shows that the likelihood of time poverty is lower for males, older people, and those working in a physical office, while higher working hours and residing in Delhi significantly increase the odds. The mean WTP calculated from the CVM analysis stands at ₹4540. Results derived from the interval-censored regression model reveal WTP being influenced by an interplay of societal norms, economic pressures, and workplace characteristics.

JEL Classification: D61, I31, J22
Keywords: Contingent Valuation; Interval Censored Regression; Time Poverty; Willingness to Pay

1. INTRODUCTION

The engine of an economy is its working population, and the way this population chooses to spend its time on a day-to-day basis deeply influences its state of functioning. Today's competitive and fast-paced economy offers people little to no time for leisure and personal pursuits, a situation for which the term 'time poverty' was coined. It is important to address this issue, as it also indirectly leads to many other problems, as people subconsciously make choices taking the limited control over time as immutable.While work provides purpose, it should not blur the distinction between making a living and living a fulfilling life. A 40-hour work week amounts to 23.8% of the total hours in a year. Unlike the self-employed, the number of working hours is usually neither a choice nor flexible for salaried employees and office-goers, resulting in them having no control over this significant portion of their time.

The knowledge economy, a sector greatly affected by this issue, hires a major portion of such workers with fixed working hours, and within this sector, the IT sector stands out as the major contributor (Thompson, 2004). The one major and often overlooked factor behind the enormous output produced by the IT sector each year is the 'time' put in by the highly skilled workforce of this sector. The sector's productivity depends on the quality of this input, determined by the efficiency of its skilled personnel, who are also very vulnerable to time poverty and its side effects, which in turn impacts their efficiency at work.

In post COVID times, the IT sector has seen some

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drastic changes in work culture. With remote work and hybrid work options becoming increasingly popular, employees are often expected to be constantly available. Such a demanding work culture can lead to reduced productivity and increased healthcare costs due to stress-related illnesses. Recent debates on the 70-hour work week have led experts to reconsider the costs and benefits of any fixed number of working hours as an over-exploitation of workers' time. Though labor laws in India, like the Factories Act 1948 discuss overtime rules in India, these are rarely followed in the IT sector citing terminology loopholes (Frontline, 2024). This is against their rights and significantly affects their physical and mental well-being. Addressing this matter is crucial for enhancing productivity and fostering sustainable workplace productivity in India.

The pioneering works on time poverty created a basic framework for this concept, addressing the inadequacy of existing money poverty measures. These works identify the presence and extent of time inadequacy and have been used as a basis by previous studies, largely to examine this issue from a gendered perspective. Gender is indeed an important determinant of differences in time use patterns. However, from an extensive review of existing literature, it is inferred that there is need for a detailed examination of other socio-demographic differences within the same gender that might correlate with shortage of time. In a country as diverse as India, analysing these intricacies is necessary for effective targeted policies that propose permanent solutions. An extensive literature review reveals that very few studies have been done in India concerning the various factors that could predict/affect time crunch.[1]

This study seeks to answer: How do socioeconomic and demographic characteristics of IT workers influence their likelihood of experiencing time poverty, and how do these factors shape their willingness to pay (WTP) for time-saving initiatives?

The research follows a three-pronged approach:

1. **Quantification**: Measure absolute and relative time poverty among IT professionals using models by Vickery (1977) and Harvey & Mukhopadhyay (2006).
2. **Valuation**: Apply the Contingent Valuation Method (CVM) to estimate WTP for a proposed Time Value Deduction (TVD) fund, a semi-hypothetical policy offering an extra day off per week.
3. **Econometric Analysis:** Use logistic and interval-censored regression to examine how demographic and socioeconomic variables affect time poverty and WTP.

The study uses a primary survey of 281 IT professionals in Cochin and Delhi and employs logistic regression to identify the determinants of absolute and relative time poverty, alongside interval-censored contingent valuation methods (Turnbull–Kaplan–Meier estimation and interval regression) to estimate willingness to pay. Results indicate that gender, age, marital status, work mode, and regional cost-of-living jointly influence both the likelihood of time poverty and the monetary value placed on buying back time.

The paper is organized as follows: Section 2 reviews the relevant literature; Section 3 outlines the data and methodology; Section 4 quantifies absolute and relative time poverty; Section 5 examines its determinants using logistic regression; Section 6 values time through contingent valuation and interval regression; and Section 7 concludes by summarizing findings, discussing limitations, proposing policy recommendations, and suggesting avenues for future research.

2. LITERATURE REVIEW

The integration of a time dimension into poverty threshold calculations was first introduced by Vickery (1978), marking a significant shift from purely income-based metrics. It was based on the key assumption that a household will be money poor if it has less than M0 amount of money, irrespective of the amount of time available, and time poor if it has less than T0 amount of time regardless of how much financial resources they have at their disposal. Vickery posited that a household with a baseline income (M0) or time (T0) can only meet the poverty threshold if supplemented with a corresponding threshold of time (T1) or income (M1) respectively, emphasizing the trade-off between market and non-market resources.

There have been a few works that utilised this basic

[1] Except for a few recent studies on time poverty and gender, like Khed et al. (2023).

framework of time poverty to improve from consumption-based poverty standards to time-adjusted ones. When the US government established the 1992 poverty threshold of $14,463 for four-person families, it assumed that the members of those families had sufficient time available for minimal household production requirements. Douthitt (1994) questions this assumption by highlighting the differences in measured poverty rates when time constraints are also considered, using data from the 1985 American Time Use Survey. The Australian Time Use Survey is used for similar calculation and interpretation purposes by Goodin et al. (2004).

Harvey and Mukhopadhyay (2006) propose a simplified framework using the Canadian General Social Survey, drawing on Ås's (1978) categorization of time into four distinct types, namely, contracted time, committed time, necessary time, and free time, and computes the time deficit (surplus) values of families of varying sizes and composition.

Necessary time is the time required to maintain oneself in terms of sleeping, eating, bathing, etc. Contracted time is time that by agreement has been set aside to undertake paid work, and one is obligated by the nature of the employment contract to allocate time to these activities as appropriate. Committed time refers to time undertaken to maintain one's home and one's family and largely incorporates unpaid work done within the household. Lastly, time spent for leisure is taken as free time.

Gender differences in time inadequacy have been analysed to a greater extent. Arora (2014) examines the nature and extent of time poverty experienced by men and women in subsistence households in Mozambique. The World Bank Group has examined Time Use and Poverty in sub-Saharan Africa from a gendered perspective. Khed et al. (2023) have examined correlations between gender and time use patterns in India.

Other aspects, like age and income, though less frequently studied relative to gender, were also explored, albeit not directly associated with examining the issue of time scarcity. A prominent example is Becker's Household Production theory (1965). Additionally, works like Najam-Us-Saqib and Arif (2012) discussed an inverted U-shaped relationship between age and time crunch.

In contemporary times, time crunch and 'busyness' are often seen as signals of productivity, success, and high status. Yet, recent scientific studies provide compelling evidence that feeling time-poor can adversely affect subjective well-being, mental health, work performance, creativity, and relationship quality (Giurge, Whillans & West, 2020).

Though there has been implicit inclusion of contingent valuation methodology (hereby CVM) as part of research on economic valuation like Ciriacy-Wantrup (1947), it was Davis (1963) who formally implemented CVM in academic research for the first time in his doctoral dissertation. He approached CVM from the point of view of public finance within the framework of a cost-benefit analysis. Following his lines, Ridker (1967) applied CVM to value air pollution mitigation methods using a hedonic pricing approach. Later on, many studies emerged using CVM for the valuation of recreational resources, a few of which include LaPage(1968), Beardsley (1971), Gluck (1974), and Randall (1983). Notably, in-person interviews were done by Darling (1973) to explore the residents' willingness to pay for the amenities of the urban water parks in California.

Based on the method of questioning used, and the nature of willingness to pay (WTP) responses recorded, various econometric models have been used so far. Kriström (1990) showed that formats like open-ended questions, payment cards, dichotomous choice (single- and double-bounded), and multiple-bounded iterative bidding (MBIB) require tailored approaches. Open-ended responses are studied using OLS or Tobit models, while payment cards and MBIB data, being interval-censored, are suited for interval regression. Recent studies like Huang et al. (2017) even explore MBIB data through survival regression in the absence of protest zero responses.

Major theoretical advancements and discussions on CVM took place side by side with the aforementioned early empirical works, which include Weisbrod (1964), Krutilla (1967), and Arrow and Fisher (1974) who, according to Richard and Hanemann (2005), suggest that "there were many potential economic effects that were not adequately, if at all, reflected in market prices." Hanemann himself has contributed significantly to the theoretical foundations of this field of research, which includes CVM for discrete responses, the neo-classical theory behind CVM, the introduction and discussion of the statistical efficiency of double-bounded dichotomous choice questions, treating biases in CVM-based surveys, and so on (Hanemann, 1985; Hanemann, 1994; Hanemann, 1999; Hanemann, Loomis, & Kanninen, 1991). Another major theoretical foundation was the development of random utility maximisation theory as the basis for CVM by Kriström (1990).

Following environmental goods, other non-market goods were also explored, particularly in healthcare. Various studies used CVM via primary surveys to value patients' waiting time, health insurance, benefits of pharmacy services, ambulance services, and so on (Acton, 1973; Reardon and Pathak, 1988; Van Den Berg, Gafni, & Portrait, 2017). Following the pioneering work of Louviere (1974), transportation became another area under the scope of CVM.

Despite its psychological significance, time is rarely conceptualized as a critical economic input in production processes, due to its intangible nature and the challenges in its quantification and valuation. Although time has been examined as an economic variable in poverty research, existing literature remains predominantly gender-focused and largely international in scope. Furthermore, the valuation of discretionary time—particularly from the perspective of salaried workers—has received limited attention within CVM-based frameworks. Thus, this study is an attempt to bridge this gap between conventional literature regarding time poverty by valuing and quantifying it, adapting the same to the Indian context while incorporating various socio-economic and demographic factors.

3. DATA

Primary survey was the mode of collection of data used in this study, a choice that suits the objectives mentioned in the previous section. The reason for the IT sector being the target group for the survey is because this sector is an important contributor to the economy at the same time being one of the most affected by time crunch. It is estimated that time crunch affects almost 80% of IT professionals worldwide (Gallup, 2020). The Knowledge Chamber of Commerce and Industry (KCCI) report also found that half of the IT employees in India work nine hours or more per day, with 43% of workers citing time crunch-induced stress as the prime reason for various health issues they struggle with. Delhi NCR and Cochin were taken as areas of study, primarily due to the two being among the largest IT hubs of the country and the logistical feasibility of conducting research in these regions. Additionally, the two distinct cultures represented by these cities could be factored into the analysis. With the population of the study standing at around 3.5 lakhs[2], the sample target, keeping in mind the logistic constraints was kept at 325.[3]

The questionnaire, as given in the appendix (refer to A-8), broadly comprised three parts. The first part was meant for the collection of various characteristics of the respondents, like age, gender, marital status, etc., which were used as variables for the econometric analysis done in sections 5 and 6. The second part asked the respondents the amount of time devoted to different activities during an average weekday. This is the data used for quantifying time poverty in section 4. Even though there is no centrally accepted classification of time, this study adopted a modified version of the basic framework made by Ås (1978) incorporating all the literature that followed. An individual's daily 24 hours is classified into four categories: necessary time, contracted time, committed time, and free time. Simple and specific questions about activities belonging to each category, adapted and streamlined for this study, were framed by referring to a detailed classification by the Department of Economic and Social Affairs Statistics Division, UN (2019).[4] Overlapping of some activities in multiple categories is also addressed in this classification to minimise double counting as far as possible. The final part of the questionnaire focused on collecting data for contingent valuation analysis detailed in Section 6.

A pre-test and pilot survey were conducted through

[2] As per the 2022 PLFS survey report and a report titled 'Investment, Growth & Development 2018-19 to 2022-23: A Land of Unlimited Opportunities', conducted by the MSME Export Promotion Council.
[3] This figure is 0.4% higher than the standard 5% margin of error and corresponds to a 95% confidence interval with a margin of error of 5.4% as per Cochran's rule (Refer to Section 7 for details).
[4] Refer to Table A-1.

self-administered Google forms and phone interviews, respectively, after which the questions were made more understandable, relevant, and specific. The primary mode of data collection for the final survey was phone interviews. 293 responses were received, and after data cleaning, the final count obtained was 281. This figure corresponds to a 95% confidence interval with approximately a 6% margin of error as per Cochran's rule, a compromise that ensures the sample size remains practical while still providing statistically reliable results for the study's objectives.[5] Table 3.1 gives a summary of respondents' basic demographic profile. T

Table 3.1: *Summary of respondents' profile*

Factor	Number of respondents (%)		
	Delhi (52%)	Cochin (48%)	Total
Age			
20+	56	55	56
30+	44	45	44
Gender			
Male	47	58	55
Female	53	42	45
Work System			
Physical	54	44	48
Other	46	56	51
Marital Status			
Married	59	57	60
Unmarried	41	43	40

Source: Authors' analysis on primary survey

4. QUANTIFICATION: QUANTIFYING TIME POVERTY

4.1. Absolute Time Poverty

Respondents' reported time spent on necessary, contracted, committed, and free activities is used to compute their time deficit or surplus, serving as a measure of absolute time poverty. The theoretical methodology used for the same is as follows:

Let each individual be represented by i. A person has 24 hours in a day. Let the necessary time spent by individual i be t_n^i. Let the time available for work (paid and unpaid) and leisure for individual i be t_r^i. Then,

$$t_r^i = 24 - t_n^i \tag{1}$$

Let the productive time spend by individual i be t_p^i. Let the time available for committed and (or) free time for individual i be t_a^i. Then,

$$t_a^i = t_r^i - t_p^i \tag{2}$$

Let t_h^i be the committed time and t_f^i be the free time spent by individual i. Let t_c^i be the combined time spent on committed and free activities. Then,

$$t_c^i = t_h^i + t_f^i \tag{3}$$

Hence, if t_c^i is greater than t_a^i, it implies individual i is time poor. In other words, individual i is time poor when $\Delta t < 0$, where

$$\Delta t = t_a^i - t_c^i \tag{4}$$

Building on these equations, we define an individual as time-poor if the time available for committed and leisure activities is less than the actual time required for them. This is expressed as a time deficit $(\Delta t < 0)$, indicating an overload of responsibilities relative to available discretionary time. This time deficit forces individuals to sacrifice either unpaid domestic responsibilities or leisure, potentially leading to increased outsourcing expenses, or long-term health and productivity losses due to chronic stress and burnout.

Table 4.1.1: *Summary of results on Absolute Time Poverty*

	Not Time Poor	Time Poor	Total
Delhi	68 (45.33%)	77 (58.7%)	145
Cochin	82 (54.67%)	54 (41.3%)	136
Overall	150 (53.4%)	131 (46.6%)	281

Note: The first row of each sub-group reports the absolute count of respondents; the second row (in parentheses) shows the corresponding percentage share within that row total.

Source: Authors' calculations

As shown in Table 4.1.1, approximately 47% of respondents were classified as time-poor. The incidence was notably higher in Delhi (58.7%) compared to Cochin (41.3%), suggesting regional disparities likely tied to work culture and commuting patterns.

4.2. Relative Time Poverty

The calculated time deficit values give an absolute measure of the time poverty of an individual. To assess whether an individual has at his or her disposal a 'social norm' amount of time to spend on personal pursuits and recreational activities, a relative measure of time scarcity is required. Individuals are classified based on relative time poverty into four groups: neither time poor nor money poor, not time poor but money poor, time poor but not money poor, and both time poor and money poor. Two relative

[5] Refer to footnote 12.

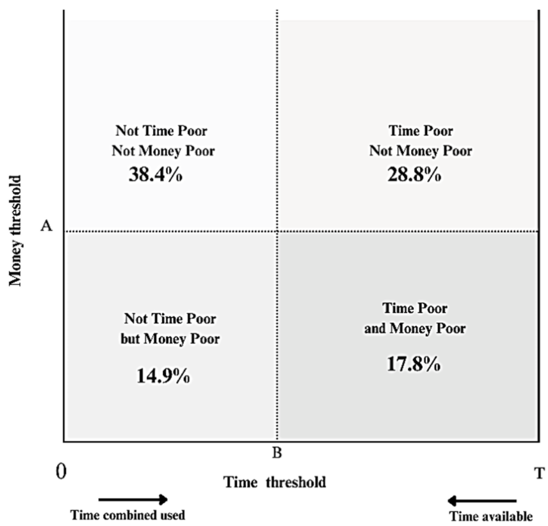
threshold values are computed based on money and time, which separate these four groups.

Calculation of the relative time poverty thresholds was done using a weighted aggregate of available time (t_a^i) values, with weights (w) based on income levels, in accordance with previous literature. The weighting scheme assigns greater influence to individuals with higher incomes, reflecting their increased capacity to substitute unpaid work with paid services. Individuals are classified as being relatively time poor if their personal combined time (t_c^i) exceeds this relative threshold amount of available time. Hence, the following inequality determines relative time poverty.

$$t_c^i = \frac{\sum_{i=1}^{n} w_i \, t_a^i}{\sum w_i} \implies Relatively\ time - poor \qquad (5)$$

The time threshold value calculated using the primary survey data was 6.57 hours. With reference to previous literature like Foster (2008), the minimum threshold for income is set at a percentage of the median income (12.5 lakh per year). The international standard for relative poverty measurement is the share of population below 60% of the median income. Hence, 60% (7.5 lakh per year) and an additional 40% (5 lakh per year) thresholds of median income as money poverty lines were employed, and the proportion of respondents in each of the four categories for both threshold values is summarised in Table 4.2.1. Additionally, figure 4.2.1 is a quadrant diagram, visually representing the results from the conventional 60% median income threshold.

Figure 4.2.2: *Proportion of respondents in different poverty categories*



Source: Authors' calculations

A notable result from these calculations is that out of the people who are money poor, a greater proportion of people are also time poor (17.8% > 14.9%), and the difference in these proportions is much more pronounced when the money threshold is set higher at 60%. This suggests that limited financial resources constrain their ability to outsource household responsibilities, reinforcing their time scarcity. At the same time, almost 30% of workers are relatively time poor even when they are able to substitute activities. These findings underscore that time poverty cannot be fully explained by income alone. To better understand the factors contributing to relative time poverty, the next section employs econometric models to examine the influence of socio-demographic and economic characteristics.

Table 4.2.1: *Summary of results on Relative Time Poverty*

Category	Individuals in poverty categories (%)	
	Under 40% money threshold	Under 60% money threshold
Neither time poor nor money poor	47.3	38.4
Time poor but not money poor	38.8	28.8
Not time poor but money poor	6.4	14.9
Both time poor and money poor	7.4	17.8

Source: Authors' calculations using primary survey data

5. ANALYSING TIME POVERTY: LOGISTIC REGRESSION ANALYSIS

5.1. Methodology

This study employs a logistic regression model to analyse the relationship between socio demographic factors and time poverty with respect to the target audience of the study. The econometric model is specified as follows:

$$P(TPS_i = 1 \mid X_i) = \frac{1}{1 + e^{-(X_i)}}$$

where

$$X_i = \beta_0 + \sum_{j=1}^{k} \beta_j \, X_{ji} + \sum_{m=1}^{p} \beta_m \, (X_j \times X_l) \qquad (6)$$

Here, β_0 is the intercept. X_{ji} represents the independent variables recorded with respect to each respondent i and includes both binary and continuous variables. β_j represents the coefficients for each independent variable. $(X_j \times X_l)$ represents the interaction terms of the model with β_m being the coefficients of the same. The detailed description along with the descriptive statistics of the variables used is presented in Table A-2 in the appendix.

The dependent variable of the study is the time poverty status of the individual, which is represented by the binary variables denoted as TPS_i indicating whether an individual is time poor (1) or not (0). The key explanatory variables include age, gender, marital status, mode of work and place of residence, all of which are represented as dummy variables. For example, D_{AGE_i} equals 1 if the individual is above 30 years old and 0 otherwise; D_{MOW_i} equals 1 if the individual is engaged in physical work and 0 otherwise, D_{POR_i} equals 1 for individuals residing in Delhi and 0 for those in Cochin, and so on. Continuous variables in the analysis include working hours (WH_i), annual personal income (API_i) annual household income (AHI_i), number of children (NOC_i), and number of earning members in the household $(NOEM_i)$. Moreover, interaction terms are included to capture potential joint effects.

The average working hour of the sample stands at 7.43 hours a day with the mean annual personal and household incomes at 12.98 lakhs and 17.16 lakhs, respectively. A slight majority of respondents are male (55.2%), married (60.1%), and reside in Delhi (51.6%). About 48.4% of the sample is engaged in physical work.

The choice of a logistic regression model is due to the dependent variable of the study being dichotomous in nature.[6] The choice of many variables is solely based on previous literature as mentioned in the literature review. The interaction terms were included based on the literature review as well as from the authors' intuition based on the engagement with the respondents to analyse the complex relationships among these factors. For example, young married mothers in the IT sector might face an added time crunch relative to their male counterparts owing to additional time spent on household chores and family responsibilities in line with patriarchal expectations. Also, the mode of work was included because of the flexibility often seen in IT jobs, which can affect time poverty either positively or negatively, making the same crucial.

Lastly, the addition of variables related to income and place of residence reflects the potential trade-offs between labour and leisure as well as the cultural aspects, respectively, thereby adding another layer of dimension to the analysis.

5.2. Results and Analysis

The result obtained after running the regression is as shown in Table 5.2.1 with model diagnostics presented in the appendix.[7] The associated ROC curve (figure 5.2.1) with the AUC value at 0.74 indicates that the model is fairly capable of distinguishing between time poor and non-time-poor individuals.

Table 5.2.1: *Results of the logistic regression model*

Variable	Estimate (SE)	Odds Ratio	% change
Intercept	-3.745 ** (1.158)	0.024	-97.636
D_{AGE_i}	-0.797 . (0.463)	0.451	-54.932
D_{GEN_i}	-0.641 ** (0.244)	0.527	-47.323
D_{MAR_i}	0.718 (0.489)	2.05	105.033
D_{MOW_i}	-0.977 * (0.466)	0.376	-62.356
D_{POR_i}	-0.579 (0.705)	0.56	-43.954
API_i	-0.0258 (0.042)	0.975	-2.547
AHI_i	-0.031 ** (0.011)	0.969	-3.052
NOC_i	-0.538 (0.417)	0.584	-41.609
$NOEM_i$	-0.0258 (0.211)	0.975	-2.547
WH_i	0.571 *** (0.129)	1.77	77.004
$D_{GEN_i} \times D_{MAR_i}$	-0.511 . (0.292)	0.6	-40.01
$D_{MAR_i} \times NOC_i$	0.558 (0.461)	1.747	74.717
$D_{MOW_i} \times D_{POR_i}$	1.238 * (0.544)	3.449	244.871
$D_{AGE_i} \times D_{MOW_i}$	0.192 (0.527)	1.212	21.167
$D_{AGE_i} \times D_{GEN_i}$	-1.209 * (0.557)	0.298	-70.15
$API_i \times D_{POR_i}$	0.033 (0.045)	1.034	3.355

Null deviance: 388.26 on 280 degrees of freedom
Residual deviance: 345.96 on 264 degrees of freedom
AIC=379.96

*** p<0.001, ** p<0.01, * p<0.05, . p<0.1

Source: Authors' calculations

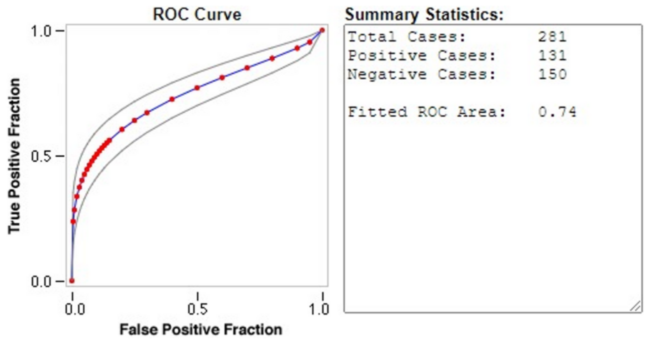
The results show that being male decreases the odds of being time-poor by 47%, while being a married male decreases the same by 40%, reflecting

[6] A probit model was also run. The results are more or less the same with respect to the logit model employed with $AIC_{\text{probit}} > AIC_{\text{logit}}$

[7] Refer to tables A-3 and A-4.

patriarchal privileges. The lack of equity in gender-based allocation of unpaid domestic work forms the major reason for increased chances of time poverty for married women (Hyde et al., 2020). Being married and aged over 30 additionally decreases the odds of being time-poor by 70%, while being 30 or older in itself decreases the odds by 54%. This particularly aligns with the Household Production Theory by Becker (1965) in addition to the explanations provided above. Empirical findings like Najam Us-Saqib and Arif (2012), which showcase an inverted U-shaped relationship derived between age and time inadequacy, further support the theory's claims.

Figure 5.2.2: *Results of the logistic regression model*



Source: Authors' visualisation

It is interesting to note that the association of AHI with respect to time poverty, though significant, is minute, at 3% only. This concerns the share of AHI, not AHI itself. Bittman, Rice, and Wajcman (2004) state that "one would therefore expect that those providing the larger share of household income would spend less time on housework and childcare." Though it is an intriguing finding that the physical office environment reduces the odds of being time poor by 62% with respect to other modes of work, there are various underlying theories to explain the same. One such theory is the Boundary Theory by Voydanoff and Nippert-Eng (1998) which posits that clear demarcation of work and household chores, like working in a physical office, reduces the overlapping and conflict of roles and enhances time management.[8]

Additionally, higher working hours increase the odds of time poverty by 77% as expected, highlighting the direct impact of work commitments on overall time management. Working in a physical office in Delhi increases the odds of being time-poor by a whopping 245%. This can be attributed to the fast-paced lifestyle and the associated drawbacks (like increased commute time and extended working hours) of a metropolitan city like Delhi in contrast to the relatively relaxed pace of work-life culture in Cochin.

This section explored the various factors influencing the likelihood of individuals being time poor. Based on these findings, policy prescriptions that are tailored for IT firms could be formulated. The following section discusses one such solution-orientated analysis based on the valuation of time.

6. VALUING TIME: CONTINGENT VALUATION METHOD

The Contingent Valuation Method (CVM) has been a popular method used to value non-market goods, primarily environmental resources. However, as mentioned in the literature review, the scope of CVM has expanded to other non-market goods, including the concept of time. The focus of this study is on the willingness to pay (WTP) for Time Value Deduction (TVD) fund for an extra day off per week. The method of questioning adopted by this study is Multiple Bounded Iterative Bidding (MBIB), in which the respondents are asked if they are willing to pay a certain amount towards the TVD fund for an extra day off per week after presenting the scenario. Based on the response towards this initial bid (yes/no), the amount is revised upwards or downwards. The detailed scenario developed for the study, along with the major strategies adopted to address biases in the survey process, has been detailed in the appendix.[9] The theoretical framework behind this study, adapted from Kriström (1990) is also discussed in the appendix (refer to A-7).

6.1. Handling WTP Data

After explaining the scenario, dichotomous choice-based questions were asked to respondents regarding their valuation using the MBIB approach with the initial bid placed at ₹ 6000 based on 10% of the average monthly income calculated from the pilot survey. The number of bidding amounts (excluding zero responses) offered was five and in equal intervals by convention. Thus, the resultant response bids by

[8] Another theory that could explain the same is the Job Demands-Resources (JD-R) Model (Demerouti et al. 2001), the framework of the same implies that Physical office environments, unlike remote mode, enhance access to resources, which help mitigate demands, improve efficiency, and ultimately reduce time poverty.
[9] Refer to Table A-5 for biases addressed and A-8 for the scenario and MBIB questions.

individuals were arranged in the form of equal intervals[10] ranging from ₹0 to ₹10,000.

Since the 10% income threshold used to set the initial bid at ₹6000 was chosen at random, this starting bid was unrelated to their actual WTP values. Thus, the randomness in the choice of the initial bid does not introduce bias into the final responses. Therefore, the stochastic nature of the bidding process is ignorable for conducting inference on the interval observations and needs no additional refinement (Heitjan & Rubin, 1991; Fernández et al., 2004). However, starting point bias is still present, a trade-off the authors were willing to accept to implement MBIB (refer to Table A-5 for details).

In CVM-based studies, zero responses are quite common as well as important. There are mainly two types of zero responses in CVM-based surveys: true zeroes and protest zeroes. True zeroes represent a genuine willingness to pay with the respondent's valuation truly at 0, as they either do not value the good or service, cannot afford to pay, or do not gain additional utility from the same. Protest zeros, on the other hand, occur when respondents state zero WTP for reasons unrelated to their actual valuation, like opposition to the payment system, the belief that the good should be provided for free, etc. Distinguishing between these two is crucial for accurate valuation and is typically done via survey questions and/or ex-post classification methods. For this study, the zero responses collected were primarily true valuation zeroes. In the phone interview process, the survey explicitly provided an option not just for a zero willingness to pay (WTP), but for respondents to explicitly state, 'I am not willing to pay anything,' thereby distinguishing genuine non-valuation from potential protest responses.

With the response data organised and accounting for the caveats mentioned above, the subsequent subsections presents the WTP estimated for this study using parametric and non parametric methods.

6.2. Mean and Median WTP

The responses are summarised in Table 6.2.1 using the Turnbull-Kaplan-Meier nonparametric approach. This estimation can only provide us the interval in which the median WTP falls, which turns out to be ₹2000-₹4000.

Table 6.2.1: *Turnbull-Kaplan-Meier Estimation Results of responses*

Bid Value Interval	Frequency (%)	Cumulative Frequency (%)	Survival Probability (%)	Density change (%)
0-0*	0.19	0.19	0.81	0.19
0-2000	0.28	0.47	0.53	0.28
2000-4000	0.04	0.51	0.49	0.04
4000-6000	0.22	0.73	0.27	0.22
6000-8000	0.11	0.84	0.16	0.11
8000-10000	0.16	1	0	0.16

**This interval represents true valuation responses*

Source: Authors' calculations

To get an exact value of the mean or median WTP, one must assume that the WTP values follow a specific parametric distribution. Based on a comparison of the log-likelihood values[11] and the skewness of the data, the Weibull distribution was chosen. Additionally, works like Carson et al. (1992) talk about the advantage and frequent reliance of assuming Weibull distribution for the same. The results of the estimation are shown in Table 6.2.2. The median WTP is estimated at approximately ₹3,834, with a mean of ₹4,540, equivalent to roughly 3.5 % and 4.2 %, respectively, of the respondents' average personal monthly income.

Table 6.2.2: *Results of Weibull Distribution Analysis for WTP Data*

Parameter	Estimate	Lower 95% CI	Upper 95% CI	Standard Error
Shape (k)	1.401	1.117	1.756	0.162
Scale (λ)	4981.272	4205.197	5900.572	430.441
N (Total Observations)	281			
Censored	281			
Log-Likelihood	-143.79			
AIC	291.581			
Median WTP	**3834.364**			
Mean WTP	**4539.739**			

Source: Authors' calculations

6.3. Factors influencing WTP: Interval Regression Analysis

The dependent variable in this case is the willingness to pay (WTP) an amount per month for an additional day off per week, which is presented in the form of intervals as a result of MBIB. The predictors chosen for the model are the same as those of the logit model. Since the WTP responses are in the form of intervals, an interval regression model is appropriate. The interval regression assumes that the unobserved WTP follows a distribution and that the observed value is only known to fall within an interval. The probability that the true WTP falls within the observed interval is:

[10] To be precise, the bids offered are (0-0), (0-2000), (2000-4000), (4000-6000), (6000-8000), and (8000-10000).

[11] $log\text{-}likelihood_{weibull} = -143.790$; $log\text{-}likelihood_{log\text{-}logistic} = -187.401$; $log\text{-}likelihood_{gaussian} = -228.409$

$$P(WTP_i) = F(U_i \mid Z_i\beta,\ \lambda) - F(L_i \mid Z_i\beta,\ \lambda)$$
where $$WTP_i\ \epsilon\ [L_i, U_i] \quad (7)$$

Here, λ represents the parameter of the assumed distribution. β is the coefficient vector, Z_i represents explanatory variables for individual i and $F(\cdot)$ is the cumulative distribution function of the assumed WTP distribution. As mentioned before, the log-likelihood[11] and AIC values of the data shows that, a weibull distribution best fits the model. The econometric specification of the Weibull interval regression model is as follows:

$$log(WTP_i) = \beta_0 + \sum_{j=1}^{k} \beta_j X_{ji} + \sum_{m=1}^{p} \beta_m (X_j \times X_l) + \epsilon_i$$

where $$\epsilon_i \sim EV1(0, \sigma)\ ;$$
$$WTP_i\ \epsilon\ [L_i, U_i] \sim Weibull(\lambda, k)\ ;$$
$$L_i > 0,\ U_i > 0 \quad (8)$$

Here, $log(WTP_i)$ represents the unobserved value of WTP. All other terms are as explained for equation 6 in Section 5. The error term (ϵ_i), is assumed to follow an Extreme Value Type I ($EV1$) distribution, which corresponds to weibull distribution. Since the Weibull model cannot handle exact zeros, a small negligible integer (₹10^{-10}) was added to true zero responses to ensure the computation of the model.

It is to be noted that zero-inflation models and double hurdle models are not explored as all zero responses recorded are associated with true valuation (corner solutions or non-use situations) and do not represent protest bids or non-participation.

6.4. Regression Results and Analysis

The results of the model are presented in table 6.3.1 as follows, with model diagnostics presented in Table A-6 of the appendix. The estimates can be interpreted in terms of their effect on $log(WTP_i)$. Since the dependent variable is in log form, a one-unit change in an independent variable corresponds to a percentage change in WTP.

As expected, gender is inversely associated with WTP; men are willing to pay about 28.5% less than women. It clearly aligns with all of the findings from Section 5.2, where the logistic regression analysis definitively showed that men encounter a lower probability of experiencing time poverty to a large degree. The alignment of these specific results sharply shows that established gender roles truly affect the allocation of time, largely affect financial decisions, and affect the amount people will pay for time-saving initiatives, such as TVD.

Table 6.4.1: *Results of Weibull Distribution Analysis for WTP Data*

Variable	**Estimate (SE)**	**t-value**
Intercept	-19.321 ** (48.21)	3.85
D_{AGE_i}	17.854 . (4.912)	3.64
D_{GEN_i}	-28.512 *** (8.103)	-3.52
D_{MAR_i}	-4.503 (1.372)	-3.28
D_{MOW_i}	9.11 (2.965)	3.07
D_{POR_i}	6.473 * (2.601)	2.49
WH_i	-1.215 . (0.298)	-4.08
API_i	4.601 ** (1.415)	3.25
AHI_i	7.922 *** (2.246)	3.52
NOC_i	-8.783 (2.48)	-3.54
$NOEM_i$	-18.954 . (5.762)	-3.29
$D_{GEN_i} \times D_{MAR_i}$	7.811 ** (2.132)	3.67
$D_{MAR_i} \times NOC_i$	-6.715 (1.793)	-3.75
$D_{MOW_i} \times D_{POR_i}$	-17.835 * (4.932)	-3.61
$D_{AGE_i} \times D_{MOW_i}$	12.924 (3.688)	3.5
$D_{AGE_i} \times D_{GEN_i}$	-0.415 ** (0.147)	-2.83
$API_i \times D_{POR_i}$	-0.1821 (0.548)	0.15
Log(scale)	1.3060 *** (0.0541)	24.15

Scale= 3.69 N=281
χ^2 = 71.41 on 16 degrees of freedom, p = 0.000
*** p<0.001, ** p<0.01, * p<0.05, . p<0.1
Source: Authors' calculations

The results show older workers are each willing to pay nearly 18% more for each time-saving measure. These results could mean there is a greater opportunity cost of time or a greater importance to work-life balance with age. However, male workers above 30 have a 0.42% lower WTP than their demographic counterpart. Though the effect size is small, this could reflect lower prioritisation of work- life balance among older men compared to women. The lower willingness to pay observed may stem from gender roles that position work as their primary identity, limited personal involvement in domestic responsibilities, which are often delegated to spouses . or domestic help and a culturally natural tendency to deprioritize leisure or self-care, all of which reduce the perceived value of time-saving interventions. Patriarchal expectations might put the burden of house chores on the females of the family, which could be another implicit yet crucial reason for the same. This is correctly strengthened by the effect of gender on WTP, as stated in the previous paragraph.

Interestingly, despite the logit model suggesting a reduced likelihood of time poverty for this group, married men show a 7.8% higher willingness to pay than their demographic counterparts. One reasonable explanation is found in the interaction of changing priorities, social expectations, and financial stability accompanying marriage. In the Indian setting, marriage is sometimes connected with more financial stability and life-stage maturity, so allowing free spending on quality-of- life enhancements. Crucially, even if married men might not be objectively time-poor, they could still be more in demand for time coordination—balancing job, family, and social obligations—which raises the apparent value of time-saving tools like TVD. Their higher WTP then reflects not desperation for time but rather the ability and will to invest in comfort and harmony inside the house. Thus, even in the absence of severe time scarcity, marriage seems to reorient financial decisions toward tools that enhance work life balance and domestic efficiency.

This justification is further strengthened as one can see significant results for API and AHI, with the latter being highly significant. The results indicate that with higher household or personal financial capacity, the probability of having a higher WTP rises around 8%, reflecting their enhanced purchasing power and ability to invest in quality-of-life improvements.

Even though the model stipulates that being in a physical office increases WTP by 9% more than other modes of work, mode of work coupled with the place of work tells us a different story. Physical workers in Delhi have a notably lower WTP, almost 18% less compared to their counterparts. This disparity likely reflects the compounding effect of higher living expenses in a metropolitan region like Delhi, where housing, transportation, and general consumer costs place substantial pressure on disposable income. Under such financial constraints, even those who recognize the value of time-saving services may deprioritize them in favour of essential expenditures. Moreover, the time–money trade-off becomes sharper: when income is stretched thin, the opportunity cost of spending on discretionary conveniences like TVD becomes harder to justify. In contrast, physical office workers in cities with lower living costs like Cochin, would not face the same budgetary pressures and may therefore exhibit a higher WTP despite comparable work demands. This suggests that regional economic context meaningfully mediates how individuals value and can act on their time preferences.

Similarly, even when higher working hours lead to increased chances of time poverty, having more working hours is negatively associated with WTP, though at marginal significance. The compensatory programs found in many companies, especially in the IT sector, where overtime can often be rewarded with performance bonuses or extra leave, help to explain this seeming paradox. Such advantages could psychologically offset the apparent weight of time loss, so enabling workers to feel sufficiently compensated for their long hours. Those who work longer hours may also create routines or coping methods that help them to normalize their limited time, so lowering the desire to pay for outside interventions like TVD. Economically speaking, the trade-off between time and money gets more complicated; employees who make more by working overtime could value income retention more than discretionary spending. Hence, despite being time-poor, these individuals may view TVD as a non-essential expense, especially when employer-provided benefits already aim to restore work–life balance.

7. CONCLUSION

This study explored time poverty among IT professionals in Cochin and Delhi, employing a mixed-methods survey based approach. By investigating a diverse set of demographic factors—not just gender— and concentrating on India's IT workforce, this study marks a meaningful advance in the field of time-poverty research. Despite certain limitations which are discussed in the subsequent subsections, the findings offer several clear insights. Nearly half of respondents (47 %) experienced absolute time poverty, and an additional 29 % faced relative time poverty despite sufficient income. Logistic regression revealed that male gender, older age, and working in a physical office significantly reduced the likelihood of time poverty, whereas longer work hours and metropolitan residence (Delhi) increased it. The contingent valuation model produced a mean WTP of ₹ 4540 (median ₹ 3834), with higher valuations among women, married and older workers, and those with greater financial capacity and lower valuations among high–cost–of–living urban workers and overtime-compensated employees.

7.1. Limitations and Policy Prescriptions

Although the UN-based categorisation was adopted for the survey regarding various activities done in a day, the same may not be foolproof to address the issues of multitasking and double counting completely, leading to a possibility of overestimation of time poverty. Additionally, there are inherent inconsistencies still pending in the categorisation (Williams, Masuda, & Tallis, 2015). Though the sample size corresponds to Cochran's rule with the same reflecting a size at a 95% confidence interval at only a 6% margin of error, there are limitations regarding the power of the study.[12] However, given the constraints of data collection and the exploratory nature of the study, this level of power is considered acceptable for the analysis of medium to large effects. Hence, the studies on similar lines would always benefit from a rise in their sample size. To mitigate these biases, future studies could consider using time diaries or experience sampling methods (ESM), which ask participants to record or log activities in real time. Additionally, leveraging smartphone-based time-tracking apps could provide passive, high-frequency data capable of capturing overlapping tasks and transitions more accurately, thereby reducing reliance on recall and improving temporal precision.

Another inherent limitation of quantifying time poverty is the abstract nature of time poverty as a concept in itself. The quantification methodology adopted by this study, like all the previous literature related to this area, is based on a theoretical framework where individuals are assumed to allocate their fixed 24-hour day into various categories. Though the monetary rationale behind the classification is accepted in academic circles, the categorisation is not fully immune from the complexity of real-world biases like reporting bias, recall bias and the subjective nature of time usage. Hence, the exact magnitude might be overestimated, but the overall direction of the findings of this study aligns with previous literature and still holds. It is more effective in capturing relative differences among various demographic groups rather than absolute magnitude. While the various solutions to curb the issue of time poverty, like paid leave, maternity leave, overtime pay, creches, and improved transport facilities, are already within the framework of the labour laws of India strengthened by various court rulings and government initiatives, it remains a persistent issue. This suggests that either these existing measures are not being effectively enforced or that they alone are insufficient in addressing the complexities of time poverty. Several factors contribute to this: lack of awareness among workers, particularly in informal or semi-formal sectors; limited enforcement capacity of labour departments; employer non-compliance; and the exclusion of certain groups (e.g., gig workers, contract employees) from formal protections. These implementation gaps dilute the impact of even well-intentioned policies.

Thus, there is a pressing need to either explore innovative solutions like the Time Value Deduction (TVD) fund for additional days off or to ensure stricter compliance with existing regulations. In practice, employers could integrate TVD into payroll, automatically allocating a small percentage of each paycheck into a time-off account, with a clear opt-out option while communicating the program as an investment in well-being and productivity. To overcome scepticism, firms should pair this with targeted awareness campaigns, early-adopter testimonials, and real-time tracking of accrued credits. Moreover, for those wary of a four-day week, unused TVD days could convert into a fixed annual allotment of paid leave or, after a vesting period (e.g. three years), be cashed out at an interest-equivalent rate. This dual-option design leverages inertia,

[12] The power analysis conducted for the study indicated a value of 0.68, which suggests a moderate risk of non detection of smaller effects (f^2 = 0.02). However, when considering larger effect sizes (f^2 = 0.15), the study achieves a power of 0.99 well beyond the ideal threshold of 0.80.

mitigates present bias, and reframes foregone wages as bankable value—building trust in TVD and a reduced-hours model over time.

More importantly, rather than the two options mentioned above, one major factor to consider in the policy design process is the role of human behaviour and decision-making, as individuals do not always behave in economically rational ways. Theories like prospect theory (Kahneman & Tversky, 1979) investigate the same in detail. In the context of our study, if workers perceive taking an additional day off (even if compensated) as a relative potential loss in terms of productivity or career progression and thereby their monetary progress in the long run, the incentive of paid time off may not be as effective as intended. Hence, policies must recheck the value proposition associated with each measure. This could include not just offering additional paid leave but also providing evidence of long-term benefits like improved productivity, better mental health, and work-life balance. Also, nudges that address this irrationality, such as default enrolment in flex-time arrangements or TVD schemes, which workers can opt out of if they choose, would improve the efficiency of such measures.

7.2. Scope for future study

Time poverty is a relatively emerging concept, especially in the context of knowledge economy workers, and thus has scope for further academic explorations. This includes applying the analysis to other segments of the working class such as blue-collar workers, gig economy participants, or healthcare professionals. More nuanced models like the spike model and double hurdle models could be incorporated to enhance the robustness of studies on the valuation of time further, particularly when dealing with survey responses that include protest zeroes. Additionally, expanding the range of variables by broadening the set of demographic, social, economic, cultural, technological, and psychological factors in future research could provide more comprehensive insights. Lastly, comparative studies across nations with different geographic and economic contexts could offer valuable cross-sectional insights, contributing to the global discussion on time poverty. Thus, in the quest for discretionary time, understanding its value may be the first step toward truly achieving it.

APPENDIX

Table A-1: *Detailed description of the categories of time used in the survey*

Major Division	Division	Group	Activity
1			Productive
	1.1		Employment related
		1.1.1	Working hours/ Average working hours (formal/informal workers respectively)
		1.1.2	Commuting time
2			Committed
	2.1		Household maintenance
		2.1.1	Cooking hours
		2.1.2	Cleaning hours
		2.1.3	Shopping for house chores
		2.1.4	Pet care hours
	2.2		Caregiving
		2.2.1	Child care hours
		2.2.2	Dependent adults (old parents/ PWD adults)
3			Necessary
	3.1		Self-care and Maintenance
		3.1.1	Sleeping hours
		3.1.2	Eating(B/L/D) home cooked meals
		3.1.3	Personal Hygiene and care
		3.1.4	Exercise (Physical or Mental)

4			Free		
	4.1			Socializing and Community practices	
		4.1.1			Meeting relatives/neighbours/friends/people you know
		4.1.2			Religious activity
	4.2			Leisure/ culture practices	
		4.2.1			Entertainment (eg: movies/series)
		4.2.2			Relaxing activities within
		4.2.3			Relaxing activities outside home
		4.2.4			Snacking
	4.3			Media	
		4.3.1			Social media
		4.3.2			Print media

Source: Adapted from International Classification of Activities for Time-Use Statistics 2016, Department of Economic and Social Affairs Statistics Division, UN

Table A-2: *Description and Descriptive Statistics of variables – Logistic Regression Model*

Notation	Type	Description	Descriptive Statistics[+]
TPS_i	Dependent	Time Poverty Status of individual *i* 1 if the individual *I* is time poor, 0 otherwise	0.466 (0.500)
D_{AGE_i}	Dummy	Age of individual *i* 1 if age > 30, 0 otherwise	0.438 (0.497)
D_{GEN_i}	Dummy	Gender of individual *i* 1 if male, 0 if female	0.552 (0.498)
D_{MAR_i}	Dummy	Marital Status of individual *i* 1 if married, 0 if unmarried	0.601 (0.490)
D_{MOW_i}	Dummy	Mode of Work of individual *i* 1 if physical, 0 if otherwise	0.484 (0.501)
D_{POR_i}	Dummy	Place of residence of individual *i* 1 if Delhi, 0 if Cochin	0.516 (0.501)
WH_i	Continuous	Working hours of the individual *i*	7.429 (1.309)
API_i	Continuous	Annual Personal Income of individual *i*	12.980 (5.896)
AHI_i	Continuous	Annual Household Income of individual *i*	17.161 (6.967)
NOC_i	Continuous	Number of children for individual *i*	0.950 (1.023)
$NOEM_i$	Continuous	Number of earning members in the family of individual *i*	1.932 (0.659)
$D_{GEN_i} \times D_{MAR_i}$	Interaction	Interaction between gender and marital status of individual *i*	-
$D_{MAR_i} \times NOC_i$	Interaction	Interaction between marital status and number of children of individual *i*	-
$D_{MOW_i} \times D_{POR_i}$	Interaction	Interaction between mode of work and place of residence of individual *i*	-
$D_{AGE_i} \times D_{MOW_i}$	Interaction	Interaction between age and mode of work of individual *i*	-
$D_{AGE_i} \times D_{GEN_i}$	Interaction	Interaction between age and gender of individual *i*	-
$API_i \times D_{POR_i}$	Interaction	Interaction between annual personal income and place of residence of individual *i*	-

[+] *This column gives the mean of each variable along with the standard deviations stated in the parenthesis*

Source: Authors' elaboration

Table A-3: *Likelihood Ratio Test – Logistic Regression Model*

Model	Residual *Df*	Residual Deviance	*Df*	χ^2 Value	P-value
Null Model	280	388.26	-	-	-
Full Model	264	345.96	16	42.3	0.0004

Source: Authors' calculations

Table A-4: *Test for Multicollinearity – Logistic Regression Model*

Variable	VIF
D_{AGE_i}	3.197
D_{GEN_i}	3.238
D_{MAR_i}	3.411
D_{MOW_i}	3.256
D_{POR_i}	7.472
API_i	3.643
AHI_i	2.401
NOC_i	8.260
$NOEM_i$	1.133
WH_i	1.120
$D_{GEN_i} \times D_{MAR_i}$	4.216
$D_{MAR_i} \times NOC_i$	7.939
$D_{MOW_i} \times D_{POR_i}$	3.558
$D_{AGE_i} \times D_{MOW_i}$	2.847
$D_{AGE_i} \times D_{GEN_i}$	3.552
$API_i \times D_{POR_i}$	6.707

Source: Authors' calculations

Table A-5: *Possible Biases in CVA and their Mitigation*

Bias	Description of Mitigation
Informational bias	Scenario designed in a way that all information were provided
Hypothetical bias	The CVA scenario built was not abstract
Sampling bias	Samples were evenly distributed for most predictor variables
Interviewer bias	Sample consisted of IT professionals who are capable of understanding the scenario
Payment vehicle bias	Avoided as the payment mechanism choice given were a deduction (not taxation), fair and less complex like PF
Starting point bias	Partially exist in the analysis, a trade-off the authors were willing to accept to implement MBIB. Partially mitigated as the starting bid was independent of true WTP values.

Source: Authors' elaboration

Table A-6: *Model Diagnostics-Interval Regression Analysis*

Test	Test Statistic	P-value	Conclusion
Model Comparison (Likelihood Ratio Test)	36.056	1.72E-06	The full model fits significantly better than the null model; predictors collectively affect the outcome.
Individual parameter significance (Wald Test)	52.927	3.93E-06	The full model is significantly better than the null model; predictors collectively affect the outcome.
Heteroskedasticity (Breusch-Pagan Test)	12.894	0.0591	Evidence of heteroskedasticity. Robust standard errors used
Multicollinearity (VIF for all predictors)	VIF ≥10 for 3 variables	-	No severe multicollinearity (VIF < 5 for majority). PCA results do not indicate redundancy[13]

Source: Authors' calculations

[13] Principal Component Analysis (PCA) results show that the first five components in itself explain 77.6% of the variance, while the figure is 93.6% for first seven components. This suggests that despite high VIF values for certain variables, the included variables contribute distinct information. Given this, the Weibull interval regression model is maintained.

A-7: *Theoretical foundation for CVM Analysis*

Each respondent's utility function includes deterministic and stochastic components:

$$u(t,m;z) = f(t,m;z) + \varepsilon_t$$

where:

m is the respondent's income,
z is a catchall variable with other socio- demographic and economic factors of the respondent,
$t = 0$ represents the absence of additional free time,
$t = 1$ represents the presence of additional free time, and
ε_t is the non-observable stochastic component.

Respondents maximize their utility by answering "yes" if their WTP is greater than the suggested price P and "no" otherwise. An individual's decision- making process can be modelled using a random utility maximization model. In other words, to the question "would you be willing to pay P?", the respondent would answer "yes" if his/her WTP was greater than the suggested price of P, and "no" otherwise, in order to maximize utility.

The respondent accepts a price P for a change in $z(t^0 \rightarrow t^1)$ if:

$$U(t^1, m - P\,; z) + \varepsilon_1 \geq U(t^0, m\,; z) + \varepsilon_0$$

A-8: *Questionnaire used for the survey*

Basic Details

- Name
- Age
- Gender: Male / Female / Prefer not to say / Other
- Occupational Status: Employed / Unemployed / Homemaker / Other
- If employed, Work Arrangement: Physical Office / Work-from-Home / Hybrid
- If employed Working Sector: Private / Public
- No. of earning members in family:
- Marital Status: Married / Unmarried
- If married, No. of children:
- Annual personal income (in lakhs) : <5 / 5-10 / 10-15 / 15-20 / 20-25 / >25
- Annual Family Income (in lakhs) : <5 / 5-10 / 10-15 / 15-20 / 20-25 / >25
- State of Residence
- Place of Residence: Metro City / Urban / Semi Urban Town / Rural

Necessary Time

- On average, how many hours do you sleep in a weekday?
- On an average weekday, how many hours do you spend eating your regular meals, including breakfast, lunch, and dinner combined?
- Do you work while you are eating? YES / NO
- If yes, how many hours (or minutes) do you spend on work while eating?
- Do you watch movies or engage in any leisure activity while eating? YES / NO
- If yes, how many hours (or minutes) do you spend on leisure activities while eating?
- On an average weekday, how many hours (or minutes) do you spend on personal hygiene (i.e., brushing and bathing) every day?
- On an average weekday, how many hours (or minutes) do you spend on exercise (physical activities like cardio or gym/mental activities like meditation or yoga)?

Productive Time

- If you are currently employed, how many hours on average do you work on a weekday?

- If you are currently employed, how many hours on average do you dedicate to office work at home on a weekday? (Write 0 if not employed)
- What is your average commute time to the workplace per day?

Committed Time

- On an average weekday, how many hours (or min) do you spend cooking for self-consumption?
- On an average weekday, how many hours (or min) do you spend cleaning your own living space?
- On an average weekday, how many hours (or minutes) do you spend shopping for your personal needs and chores?
- On an average weekday, how many hours (or minutes) do you spend caregiving for your children? (Write 0 if not applicable). On an average weekday, how many hours (or minutes) do you spend caregiving for your dependent adults (old parents/PWD adults)? (Write 0 if not applicable)

Free Time

- On an average weekday, how many hours do you spend meeting and conversing with your relatives/ friends/neighbours either in person or via phone/internet (excluding work-related conversations/ meetings)?
- On an average weekday, how many hours (or minutes) do you spend with your pets?
- On an average weekday, how many hours (or minutes) do you spend on social media (Facebook/YouTube /Instagram etc.) and print media (newspaper/books/magazines)?
- On an average weekday, how many hours (or minutes) do you spend for entertainment, like going and watching a movie at a theatre or watching movies/series on television/OTT?
- On an average weekday, how many hours (or minutes) do you spend travelling/hanging out/sightseeing etc.?
- On an average weekday, how many hours (or minutes) do you spend in relaxing activities within the home like skin care, music, gardening, journaling, religious prayers, etc.?
- On an average weekday, how many hours (or minutes) do you spend in relaxing activities outside of home, like eating out or snacking?

Contingency Valuation (Please read the scenario and answer the questions that follow).

Scenario:

"Imagine a new policy called the Time Value Deduction (TVD) fund, similar to the Provident Fund (PF), where a fixed amount is deducted from your monthly salary in exchange for reducing your working hours by one day per week. The amount paid under this scheme would be used to cover the salary of additional employees who would be hired to compensate for the reduced working hours. This policy aims to provide employees with extra free time that could be used for personal, family, or leisure activities, ultimately improving work-life balance."

MBIB Questions:

- Then, will you be willing to pay the amount? YES/NO
- If yes will you pay 6000 INR per month for an extra free day per week? YES/NO
- If yes, how much will you be willing to pay per month for an extra hour of free time each day? 6000 only and no more / Up to 8000 / Up to10000
- If no, what is the maximum amount that you will be willing to pay per month for an extra free hour each day? Up to 4000 / Up to 2000 / 0

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