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Choice and allocation characteristics of faculty time in Korea: effects of tenure, research performance, and external shock

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Abstract

Academics generally should meet *both* teaching duty and research performance requirements. Since their work time is finite, academics need to allocate time for research, teaching, and other types of work. This means that universities or governments might enhance the efficiency of their faculty systems or educational policies by understanding academics' preferences for choice and allocation of their work time. We analyzed the work time allocation preferences of 450 Korean academics in science and engineering fields based on the multiple discrete–continuous extreme value (MDCEV) model. We classified work time into either of research, teaching, or other tasks and investigated the relationship between academics' preferences in choosing and allocating their work time and faculty system (e.g., tenure), individual characteristics (e.g., research productivity) and external shock (e.g., COVID-19). Analysis results show that academics with either of tenure, higher research productivity, or commercialization experience preferred to allocating their work time firstly to research, i.e., rather than to teaching or other tasks, while this was not the case for the academics after the pandemic. In general, academics appeared not to prefer allocating their work time firstly to teaching. Implications of our study are twofold. First, the higher education sector needs to incentivize academics' teaching time allocation for enhanced effectiveness of education. Second, universities and governments urgently need systems and policies to facilitate academics' research time allocation for enhanced research productivity as we find deteriorated preference for research time allocation after COVID-19.

Keywords Faculty · Time allocation · Discrete choice model · Research · Education

JEL Classification C35 · I23 · J22

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Introduction

Research output is of foremost importance to academics because it determines their job stability in most cases (e.g., Harter et al., 2011; Kasten, 1984) in addition to their social and economic value (e.g., Fairweather, 2002). Having been considered as a significant input factor to the research output, research time has also been closely related to job satisfaction of academics (Barham et al., 2014).

However, an academic with a balanced workload (e.g., research, teaching, and so forth) cannot commit all the work time[1] to research. An academic, considering both institutional requirements and individual environments, allocates his or her work time to perform administrative work as well as research, teaching students, and sometimes participating in non-academic activities (Barham et al., 2014; Bentley & Kyvik, 2013; Harter et al., 2011).

Previous studies reported that such work time allocation of an academic is affected by various factors. They include incentives provided by the university, e.g., tenure and promotion, (Bentley & Kyvik, 2013; Link et al., 2008), personal environment and research productivity (Barry et al., 2003; Bellas & Toutkoushian, 1999; Bentley & Kyvik, 2013; Deryungina et al., 2021; Kyvik & Olsen, 2008; Kyvik & Teigen, 1996; Long, 1990; Probert, 2005), research performance such as commercialization (Barber et al., 2021; Barham et al., 2014; Bellas & Toutkoushian, 1999; Kyvik & Teigen, 1996) and exogeneous shocks like COVID-19 (Barber et al., 2021; Kubota, 2021; Myers et al., 2020).

However, the previous studies have limitations in that they do not reflect academics' choices among types of work time such as research, teaching, and other tasks. While some studies took qualitative approaches (Kyvik & Olsen, 2008; Myers et al., 2020), most studies depended on OLS-based regression approaches to identify academics' time usage (Barham et al., 2014; Bentley & Kyvik, 2013; Harter et al., 2011; Link et al., 2008). This means that most of the previous studies lack considerations on academics' choices of alternative work types, e.g., teaching or research. Classical discrete and discrete–continuous choice models (e.g., Train, 2009) can analyze choices among alternatives. However, those choice models assume mutual exclusivity where research, teaching and other tasks are perfectly substitutable. Since most academics are obligated to teach students and perform administrative works, the choice models do not appear realistic for academics. Furthermore, they are incapable of modelling allocation of finite resource and of diminishing marginal utility. (Bhat, 2005, 2008) To address both the limitations of continuous time usage and choice models with heterogeneity (i.e., distributions of marginal utilities) and global maxima, we implemented the mixed multiple discrete–continuous extreme value (MDCEV) model (Bhat, 2005, 2008).[2]

In this study, we modeled the allocation of academics' work time classified into either of research, teaching, or other tasks. Based on the model, we analyzed the relationships between academics' choices and time allocation and demographic characteristics, research performances, and exogeneous shocks e.g., COVID-19. Since estimation of the mixed MDCEV model with classical maximum likelihood methods does not seem feasible due

[1] While previous studies showed that work time of an academic is determined by his or her personal environments such as childcare (Barber et al., 2021; Bentley and Kyvik, 2013; Kyvik and Teigen, 1996; Long, 1990; Siegel and Guerrero, 2021), our study focuses on work time. In a similar vein, our study considers the work time of academics rather than students' (e.g., Schmidt, 1983).

[2] As it is a discrete choice model, use of the MDCEV model means the relative preference of a choice to another.

to the complicated calculation, we implemented the Bayesian approach (Train, 2009). The advantages of the Bayesian method include the ability to solve local optimal solution problems using the initial value and freedom from the local maximum problem, for which the maximum likelihood estimation methods are hardly suitable.

The next section of the paper briefly reviews the previous literature regarding the academics' time allocation. Section 3 considers the effects of key factors such as institutional benefit (e.g., tenure) and individual characteristics (e.g., research productivity) on academics' choice and allocation of work time. Section 4 outlines the framework for the mixed MDCEV model of time allocation and its Bayesian implementation and describes our model, data source and sample used. Section 5 provides and discusses empirical results. The final section concludes the paper with policy implications and limitations of our research.

Previous literature

Time allocation of academics has been one of research interests across fields and disciplines from economics and management science (Gautier & Wauthy, 2007; Juster & Stafford, 1991; Toutkoushian, 1999) to higher education and human resource planning (Bowen & Schuster, 1986; Braxton & Berger, 1996; Colbeck, 1998; Link et al., 2008; Massy & Zemsky, 1994; Milem et al., 2000; Singell Jr, et al., 1996). These previous studies can be categorized into relationships between academics' time allocation and either of the policies of the institution, individual characteristics, or exogeneous shock.

Regarding institutional policies, time allocation studies appear two-fold. First, studies tackled academics' time allocation as related to individual "pull factors," such as tenure and rank (thus promotion). Singell Jr. et al. (1996) found a negative correlation between academics' tenure and time weight for research. Similarly, Link et al. (2008) reported a decrease in weight of research in the work time of tenured US academics in the science and technology fields. Harter et al. (2011) and Barham et al. (2014), used surveys of US economic (from '95 to '05) and US agriculture and life science (from '79 to '05) academics to find that assistant professors tend to allocate more time to research (i.e., less in teaching or administrative works) than do full professors. Second, studies investigated academics' time allocation as related to institutional "push factors," such as administrative pressure (Clark, 1987; Leišytė et al., 2010), policies (Hornibrook, 2012), or entrepreneurship (Allen et al., 2007; Bercovitz & Feldman, 2008), that influenced the academics' preferences, e.g., for grants and contracts. For instance, Anderson and Slade (2016) reported that the academics' time allocation for even uninteresting grants and contracts increased with a decrease in their job satisfaction in response to administrative pressure.

Another factor that can influence academics' time allocation may be the type of institution, e.g., research universities vs. liberal arts colleges (Bowen & Schuster, 1986; Massy & Zemsky, 1994; Milem et al., 2000). Bowen and Schuster (1986) noted that academics at research universities invested in research time three times more than their colleagues at liberal arts colleges. On the contrary, Massy and Zemsky (1994) found that, regardless of institution type, academics preferred time allocation to research more than time allocation to teaching and other tasks, although more variation in teaching time was found at liberal arts colleges than at research universities. They attributed the preference for time allocation to research to the nature of the academic reward structure and the professionalization of faculty work. This appears to be in accordance with the results of Milem et al. (2000), who found that academics' time allocation to research increased over time based on academic surveys accumulated for about 20 years.

There have been mixed reports on the relationship between academics' time allocation and their individual characteristics. Many studies focused on personal environments, such as female researchers' allocation of less time to research due to family business, e.g., childcare (Singell Jr. et al., 1996; Creamer, 1998; Bellas & Toutkoushian, 1999; Sax et al., 2002; Barry et al., 2003; Probert, 2005). There also have been several studies in search of relationships between academics' time allocation and individual characteristics including age and gender. Singell Jr. et al. (1996) found a positive correlation between academics' age and time weight for teaching. Link et al. (2008) reported a decreased weight of research in the work time of female US academics in the science and technology fields. Harter et al. (2011) found from the surveys to US economic academics from '95 to '05 that male researchers tend to allocate more time to research than do female researchers. In contrast, based on long-term surveys from '82 to '01, Kyvik and Olsen (2008) found no significant relationship between time allocation and individual characteristics, although they found Norwegian academics allocate time, in the following order of lecture, research, administrative, and other works. After analyzing multinational surveys on 64,029 academics, Bentley and Kyvik (2013) reported similar absence of a statistically significant relationship between time allocation and individual characteristics.

There also have been time allocation studies regarding academics' individual research productivity. Several studies assumed that more time allocated for research resulted in greater chances for paper publication or commercialization. Libaers (2012) found from the surveys on the US academics that an increase in research time weight and commercialization performance were correlated positively. Based on surveys to US agriculture and life science academics from '79 to '05, Barham et al. (2014) reported that research time and paper publication performance were correlated positively. Rahmandad and Vakili (2019) reported increased paper publication with increase in research and a decrease in publications with increased teaching or administration. On the other hand, a few studies have tackled the exogeneous effect, e.g., COVID-19, on academics' research productivity. For instance, Barber et al. (2021) found that academics increased the weight of teaching over that of research in their work time after COVID-19 based on a multinational survey including students and academics.

Of special concern should be academics' commitment and thus their time allocation to teaching. Various social distancing measures, e.g., lockdown, to deal with the COVID-19 contagion practically forced academics to instantly switch their face-to-face classes to online. Pre-pandemic studies had already reported that online classes require more preparation than their face-to-face counterparts (Bolliger & Waslik, 2009; Harber & Mills, 2008; Lee & Busch, 2005; Oyarzun et al., 2020; van de Vord & Pogue, 2012). However, similarly to the exogeneous effect studies on research productivity, very few reports have examined academics' choices for teaching time allocation, while pedagogical aspects were changed with technological innovation catalyzed by COVID-19 (e.g., Nuere & de Miguel, 2021; Rapanta et al., 2021; Skulmowski & Rey, 2020).

Most previous studies (e.g., Barham et al., 2014; Bentley & Kyvik, 2013; Harter et al., 2011; Link et al., 2008) focused on the phenomenological relationship between academics' time allocation and their characteristics. Despite their meaningful implications, previous studies paid little attention to academics' choices on work type, e.g., research and teaching. It is the discrete choice model (e.g., Train, 2009) that can describe academics' choices of work type. However, use of the discrete choice model assuming independence of irrelevant alternatives, e.g., implementing multinomial logistic regression approaches, is not suitable for allocation of finite resources (Ahn et al., 2008; Bhat, 2005, 2008) such as work time. Furthermore, previous studies frequently implemented single-equation-based regression methods, which are likely to be vulnerable to endogeneity. Therefore, a different approach is required (1) to reflect academics' time allocation within the boundary conditions of (physically) finite work time and (2) to implement diminishing marginal utility with allocation of time (Table 1).

Propositions

The purpose of this study was to investigate the choices of academics regarding time allocation to research and other activities over teaching given individuals' tenure, their characteristics, and the impact of COVID. For academics research time is significant as it represents job satisfaction as well as the quantity and quality of research output (Barham et al., 2014). However, academics typically are not able to allocate 100% of their work time to research due to teaching and administrative responsibilities. (Barham et al., 2014; Bentley & Kyvik, 2013; Harter et al., 2011) In other words, academics need to set priorities on work type alternatives, e.g., research and teaching, and allocate time accordingly. Time allocation of academics is likely to be affected by various factors. Correspondingly we considered (1) institutional benefit policies such as tenure and promotion (Harter et al., 2011; Kyvik & Olsen, 2008; Link et al., 2008; Singell Jr. et al., 1996), (2) individual characteristics including research productivity (Barham et al., 2014; Libaers, 2012; Rahmandad & Vakili, 2019) and (3) exogeneous shocks like COVID-19 (e.g., Barber et al., 2021).

Tenure

Academics can maximize time utility by allocation (Bentley & Kyvik, 2013; Kyvik & Olsen, 2008; Stephan & Levin, 1992). For example, famous academics, finding diminished utility with research, will allocate less time to research and more time to other activities to help attain honor or prestige, e.g., positions such as consulting (Bentley & Kyvik, 2013; Kyvik & Olsen, 2008). In this regard, tenured academics have been reported to allocate less time to research. (Barber et al., 2021; Bentley & Kyvik, 2013; Gautier & Wauthy, 2007; Kyvik & Olsen, 2008; Link et al., 2008) The seniority burden hypothesis (Zuckerman & Merton, 1972) anticipates that more experienced academics are likely to allocate more time to non-research tasks such as administrative or evaluation tasks. As a result, the hypothesis supposes decreased time allocation to research. However, academics have become more likely to focus on research and publication activities than on teaching (e.g., Cadez et al., 2017; Massy & Zemsky, 1994; Young, 2006). Such a tendency is related to the reward structure of academic institutions favoring research over other types of academic activities (Massy & Zemsky, 1994). On one extreme, academic institutions can use so-called "publish or perish" evaluation strategies (Hattie & Marsh, 1996; Massy & Zemsky, 1994). Correspondingly, tenured academics would stick to allocating more time to research than to teaching (Link et al., 2008), because further research performance could make them more prestigious (e.g., Bentley & Kyvik, 2013). Therefore, we set up the propositions as follows:

> (Proposition 1a) Tenured academics will prefer research (to teaching) in allocation of work time.

Table 1 Summary of previous studies

Authors (year)	Time allocation alternatives	Sample	Estimation	Key findings
Singell et al. (1996)	Teaching, research, service, leisure	(US) 1409 tenured arts and science faculty	Multinomial logit (time in percent)	The older academics allocated more time to teaching and less time to research Found dependence on rank, field, marriage, gender, etc
Kyvik and Olsen (2008)	Teaching, research, admin, external	(Norway) 1,585('82)-1,967('01) academic staff	None (qualitative)	Time allocation preference order of teaching, research, admin, others did not seem to depend on age, etc
Link et al. (2008)	Teaching, research, grant writing, service	(US) 1365 scientists and engineers	OLS/GLM (time in hours)	Tenured academics allocated less and more time to research and service, respectively Women spent more time on service while less on research
Harter et al. (2011)	Teaching, research, service	(US) 1696 ('95-'05, in total) economics instructors	OLS (time in hours)	Male and assistant professors allocated more time to research than to teaching compared to female and full professors
Libaers (2012)	Teaching, research, service, consulting	(US) 1795 academic scientists	Poisson regression (time in percent)	Allocating more time on research and non-university-related service increased chances of technology commercialization
Bentley and Kyvik (2013)	Teaching, research, service, admin, others	(US & multi.) 64,029 full-time faculty	OLS (time in hours)	Academics' preference to allocate research time was due to individual motivation (i.e., interest in research, supporting the "sacred spark" theory)

Table 1 (continued)

Authors (year)	Time allocation alternatives	Sample	Estimation	Key findings
Barham et al. (2014)	Teaching, research, admin, extension appt	(US) 589('79) to 640('05) agricultural/life scientists	Fixed effect (time in percent)	Persistent decrease in research time from'79 to'05 Assistant professors spent more research time, etc
Rahmandad and Vakili (2019)	Teaching, research, administration	(US) 116,607 ('95-'05, in total) from 194 universities	ABM/OLS	The more research time, the more publication The more administration and teaching time, the less publication
Barber et al. (2021)	Teaching, research, childcare, chores, leisure, sleep	(multinational: 55% US, 25%EU) 731 faculty, 277 students	Ordered logistic (5-points Likert)	With COVID-19, academics allocated more time to teaching than to research

(Proposition 1b) Tenured academics will prefer working on other tasks (to teaching) in allocation of work time.

Individual characteristics

There have been very few studies, to the authors' knowledge, on the relationship between the number of R&D projects and allocation of work time. Fox and Mohapatra (2007) reported that academics involved in more projects were likely to perform better (e.g., more publications) by allocating more time to research (Fox & Mohapatra, 2007; Kao & Pao, 2009). On the other hand, two things need to be considered for time allocation to other tasks. First, operation of many R&D projects can cause a lack of time per project in such a manner known as the "greedy algorithm" (e.g., Coviello et al., 2014). A larger number of R&D projects require more administrative work, e.g., preparation and finalization of documents. In addition, the decrease in time for each project is likely to lower the academic's motivation to perform the project (Dewatripont et al., 1999). Second, figuratively described as "firefighting" (Bohn, 2000; Repenning, 2001), researchers often need to concentrate resources such as time and budget on the most urgent projects, i.e., those with higher priority.

(Proposition 2a) Academics with a larger number of R&D projects will prefer research (to teaching) in allocation of work time.
(Proposition 2b) Academics with a larger number of R&D projects will prefer other time (to teaching) in allocation of work time.

It has been reported that research time is closely related to research productivity (Marsh & Hattie, 2002; Olson & Simmons, 1996), in addition to production mechanism (e.g., physical and psychological health of researchers) and institutional effects (e.g., financial status and tenure, etc.) (Barber et al., 2021). Our work considers journal paper publication as one of the most representative indicators (Fairweather, 2002; Hattie & Marsh, 1996; Ladd, 1979; Way et al., 2019). Similarly with the number of research projects, we postulate that time allocation for other tasks is related to the number of journal publications.

(Proposition 3a) Academics with a larger number of journal publications will prefer research (to teaching) in allocation of work time.
(Proposition 3b) Academics with a larger number of journal publications will prefer other tasks (to teaching) in allocation of work time.

Another important indicator of researcher's R&D performance is commercialization. In that respect, R&D is considered a precondition of commercialization. Agrawal (2006) reported that an increase in research time imparts greater chances for successful commercialization based on the technology transfer (to the private sector) cases. Kruger et al. (2020) showed that pre-pandemic productivity was correlated closely to post-pandemic research output.

(Proposition 4a) Academics with commercialization experience will prefer research (to teaching) in allocation of work time.

Commercialization frequently is based on technology transfers from public sector entrepreneurship (e.g., Leyden & Link, 2015; Audretsch & Link, 2016). However, research administration also plays an important role in successful technology transfer. For instance, bureaucratic tasks are necessary in collaborative R&D between university and industry and thus they consume researchers' work time.[3]

(Proposition 4b) Academics with commercialization experience will prefer other tasks (to teaching) in allocation of work time.

Exogeneous effects

Various exogenous effects can be responsible for academics' choice and allocation of work time. For example, "period effects" or historical context in which the survey is undertaken (Riley et al., 1972) can be crucial to time allocation of academics. Our work considered the COVID-19 pandemic as an exogeneous effect. A number of studies revealed a wide spectrum of reconfigurations in R&D due to the pandemic, e.g., strengthened commercialization of non-basic research with the COVID-19 (Kubota, 2021; Siegel & Guerrero, 2021). These studies reported a decrease in academics' research time (Barber et al., 2021; Cui et al., 2021; Myers et al., 2020) with a devastating decrease in research activities reported in the US and Europe (e.g., Myers et al., 2020) due to physical disruption of faculties because of lockdown.[4] Childcare also can be a key source of such disruption of research work time and thus productivity (e.g., Barber et al., 2021).

Although Korea has not experienced lockdown, the Korean government has implemented various social distancing measures (Korea Ministry of Education, 2021). For instance, the government removed the restrictions on the number of remote classes that universities can offer, which had been regulated below 20% of total classes (Ko, et al., 2021). As a result, the online classes at Korean universities increased by 27 times between 2019 and 2020 (Higher Education in Korea, 2021). However, online teaching requires extra resources including time for preparation and effective deployment (Ali, 2020; Bolliger & Waslik, 2009; Gloria & Uttal, 2020; Harber & Mills, 2008; Lee & Busch, 2005; Oyarzun et al., 2020; Rapanta et al., 2021; van de Vord & Pogue, 2012). In other words, academics were forced to prepare online teaching and implement it in their online classes. Considering the finite resources available and in order to keep up their research performance, such a drastic change in online teaching requirements is likely to cause academics to show stronger time allocation preferences for teaching.

(Proposition 5a) After COVID-19, academics will prefer teaching (to research) in allocation of work time.
(Proposition 5b) After COVID-19, academics will prefer teaching (to other tasks) in allocation of work time.

[3] An increase in time for other tasks does not necessarily mean higher probability of successful commercialization. This is because "time for other tasks" does not only include time for R&D consulting or attending to related conferences but also time for administrative works (Libaers, 2012).

[4] For instance, Myers et al. (2020) reported that, while only 5% of scientists worked less than 42 h per week before the pandemic, the proportion increased nearly sixfold to 30% during the pandemic.

Description of the model and data

The MDCEV model

Among various multiple discrete continuous mathematical models (e.g. Bhat, 2005, 2008; Kim et al., 2002) we implemented MDCEV to analyze the choices between research, teaching and other tasks and their *simultaneous* allocation of time.

For simultaneous implementation of alternative choices with allocation of resources per alternative and diminishing marginal utility with increased resources input, the Kuhn-Tucker approach using the first-order condition for constrained random utility maximization including corner solutions was proposed (Bhat, 2005; Kim et al., 2002). However, applications of multiple discrete continuous mathematical models based on the Kuhn-Tucker approach are scarce because of the need for multi-dimensional integration to calculate their likelihood functions. By introducing a multiplicative log-extreme-value error term into the utility function, the MDCEV model provides the discrete–continuous probability of using the given levels of the alternatives in a closed form, which is advantageous for decreasing calculation time (Bhat, 2005, 2008; Kim et al., 2002). As an extension of the single discrete–continuous models (Arora et al., 1998; Chiang, 1991; Chintagunta, 1993; Dubin & McFadden, 1984; Hannemann, 1984), the model in the single discreteness case is reduced to the multinomial logit choice model. Furthermore, the model can implement heteroskedasticity and correlation in unobserved characteristics affecting the demand for different alternatives (Bhat, 2005). Another advantage of our approach includes the ability to analyze heterogeneity of respondents using the mixed MDCEV model assuming distribution of the coefficients ($\beta' s$) of marginal utility (Ahn et al., 2008; Bhat, 2008). In this regard, the MDCEV model (Bhat, 2005, 2008) is advantageous in the calculation time of coefficients because the model provides the probabilities for the final choices for alternatives and their allocations in a closed form.

According to the MDCEV model (Bhat, 2005, 2008), consumer i's utility of choosing j and using m_j is given as the sum of baseline utility $\psi\left(x_j\right)$ and continuous consumption utility,

$$U_i\left(m_1, \dots, m_J, 0, \dots, 0\right) = \sum_{j=1}^{K} \psi\left(x_j\right)\left(m_j + \gamma\right)^{\alpha_j} \tag{1}$$

In Eq. (1), γ corresponds to a translation parameter, i.e., there exists a corner solution if $\gamma \neq 0$. α_j is a marginal utility parameter such that $0 \leq \alpha_j = \left\{1 + \exp\left(-\delta_j\right)\right\}^{-1} \leq 1$, while $\psi\left(x_j\right)$ can be expressed as

$$\psi\left(x_j, \epsilon_j\right) = \psi\left(x_j\right) \exp\left(\epsilon_j\right) = \exp\left(\beta' x_j + \epsilon_j\right) \tag{2}$$

Since γ_k and α_k cannot be identified simultaneously, one of each is fixed for estimation of the other (Bhat, 2005).

Following Bhat (2005), the probability corresponding to consumer i's choices of alternative j and its usage m_j, when the total number of alternatives is K and the actual choices are made to J alternatives, takes a compact closed form of

$$P\left(m_2^*, m_3^*, \dots, m_j^*, 0, \dots, 0\right) = \left[\prod_{i=1}^{J} c_i\right]\left[\prod_{i=1}^{J} \frac{1}{c_i}\right]\left[\prod_{i=1}^{J} \frac{\exp\left(V_i\right)}{\left(\sum_{j=1}^{K} \exp\left(V_i\right)\right)^J}\right](J-1)! \quad (3)$$

where $c_i = 1 - \alpha_i/m_i^* + \gamma$ and $V_j = \beta'^{x_j} + \ln \alpha_j + \left(\alpha_j - 1\right) \ln \left(m_j^* + \gamma\right)$.

To implement heterogeneity among respondents, we introduced the mixed MDCEV model assuming the coefficients (β's) of marginal utility have their distributions (Ahn et al., 2008; Bhat, 2008). According to the mixed MDCEV model, Eq. (3) becomes

$$\tilde{P}_n = \int \left\{\left[\prod_{i=1}^{J} c_i\right]\left[\prod_{i=1}^{J} \frac{1}{c_i}\right]\left[\prod_{i=1}^{J} \frac{\exp\left(V_i\right)}{\left(\sum_{j=1}^{K} \exp\left(V_i\right)\right)^J}\right](J-1)!\right\} f\left(v_n|\theta\right) \mathrm{dv}_n \quad (4)$$

In fact, distributions among the coefficients of marginal utility means that the variations of utility can be estimated. For instance, a relatively large variation with statistical significance indicates that respondents' preferences span a sufficiently large range. However, estimation of the mixed MDCEV model is structurally complicated with lots of coefficients, an alternative draw method is recommended over the typical random draws (Bhat, 2005). In this regard, following Bhat (2005), we implemented quasi-random Halton draws.

We also implemented the Bayesian method to overcome the limits of the maximum-likelihood estimation (MLE) method. The Bayesian method is free from the vulnerabilities of the MLE method such as erroneous estimation of maximum likelihoods depending on initial values (Train, 2009). The results of Bayesian estimation can also be transformed into classical estimation results, which are convenient for comparing estimation results. Furthermore, even with use of fewer boundary conditions, the Bayesian method is superior in terms of efficiency and consistency to the classical counterparts. The Bayesian method is free from the local maximum problem because it guarantees the global maximum while MLE does not.

However, analytic approaches for the Bayesian method are not readily available. It is a typical practice to implement a Monte Carlo simulation with Gibbs sampling (Allenby & Rossi, 1998; Huber & Train, 2001; Train, 2009). The schematic of the so-called Markov Chain Monte Carlo (MCMC) simulation is as follows (Train, 2009). Firstly, a Markov chain is defined based on the posterior distribution per draw. Secondly, a posterior distribution of parameters converging on the marginal distribution is induced from the continuous sampling draws at the conditional probability distributions connecting each chain. Finally, the means of those posterior distributions are used as the estimation of the parameters. We followed Train (2009) for the MCMC-based Bayesian estimation of our MDCEV model. To estimate the parameters in the model, we used the latter 10,000 draws from 20,000 draws through Gibbs sampling (Huber & Train, 2001; Train, 2009). We discarded the former 10,000 draws to remove the initial value effect. To interpret each estimated parameter from a classical perspective, we used the mean and variance from 2000 draws from the distribution of the parameter (Shin et al., 2012).

Variables

Our study defines the work alternatives for work of an academic as research, teaching and others. We set alternative 1 as research, which frequently is regarded as the essential mission of an academic (e.g., Kyvik, 2013; Thomson & Gunter, 2011). We do not include teaching of graduate students and writing R&D grants or proposals into research, which we designate to teaching and other tasks, respectively.

We set alternative 2 as teaching, which often is considered the essential role of an academic (e.g. Finkelstein, 1988). However, our study does not censor teaching time (i.e., not to neglect a response even if its teaching time is less than such a minimum requirement) because we did not discern whether a respondent was on sabbatical leave or not.

We set alternative 3 as any other tasks excluding research and teaching. Alternative 3 is not the essential role of an academic, but the task might be necessary for the faculty operation or the academic's personal interests. Examples of alternative 3 include administrative work, works due to assignment to a position, or external activities for the academic's interests (e.g., R&D consulting for a private company).

As an attribute variable describing the alternatives, time allocated to research, teaching or others (t_k) includes only the alternative constant. To identify the estimated alternative constants, alternative 2 (teaching) was set as the baseline.

For explanatory variables, we introduced whether an academic has tenure or commercialization experience and the annual mean of the number of R&D projects and journal publications as his or her individual characteristics. The annual mean corresponds to the 5-year average by 2019, i.e., before the COVID-19 pandemic. For identification of estimation results, the variables were input as interaction terms with variables for the alternatives (Table 2).

The final estimating equation follows is:

$$\begin{aligned} V = \sum_{k \neq 2} (&\beta'_{1k} A_k + \beta'_{3k} A_k \times T + \beta'_{4k} A_k \times N_{\mathrm{PRJ}} \\ &+ \beta'_{5k} A_k \times N_{\mathrm{PUB}} + \beta'_{6k} A_k \times B + \beta'_{7k} A_k \\ &\times \mathrm{COVID}) + \sum_{k=1}^{3} \left(\alpha_k - 1\right) \ln\left(t_k^* + 1\right) \end{aligned} \tag{5}$$

Survey and data

We conducted a survey to analyze academics' time allocation behavior. Between September and October 2020. A professional survey firm[5] administered the survey to 450 academics. All 450 academics were professors of science, technology, engineering and mathematics (STEM) and had experience as a principal investigator (PI) of at least one national R&D project in the last 5 years. To represent the entire PI population with reasonable accuracy, we implemented purposive quota sampling to extract respondents according to gender, age, and research field.[6]

The survey data are summarized in Table 3. Of the respondents, 90% of the responses were from male academics and 48% and 34% of the respondents were in their 40s and 50s, respectively. The 53% and 18% worked in the engineering and natural sciences, respectively, while the other 28% were in the agricultural and life sciences. The portion of tenured

[5] Performed by Gallup Korea Research Institute (https://www.gallup.co.kr, in Korean).

[6] Considering the sample size (450 academics), we simplified the categorization of the STEM field as either of engineering, natural sciences or agricultural and life sciences.

Table 2 Construction of the variables for this study

Variables	Denoted by	Description
Time allocation for alternative	Research (t_1)	Time allocation for research (including teaching graduate students and writing grants, etc.)
	Teaching (t_2)	time allocation for teaching (mostly lecture; excluding teaching graduate students)
	Others (t_3)	time allocation for other tasks (administrative works, etc.)
Alternative	ASC|res (A_1)	1 for research; 0 otherwise
	ASC|etc. (A_3)	1 for others; 0 otherwise
Individual and research capability characteristics	T	Tenure dummy: 1 for tenure; 0 otherwise
	N_{PRJ}	Mean number of project involvements (in the recent 5 years before COVID-19)
	N_{PUB}	Mean number of papers published (in the recent 5 years before COVID-19)
	B	1 for commercialization (in the recent 5 years before COVID-19); 0 otherwise
External effect	COVID	0 and 1 for before- and after the pandemic, respectively

In addition to the variables above, age, gender, and research field (engineering, bio-agricultural, or natural sciences) were introduced as control variables

Table 3 Basic statistics regarding the variables

Variable	Details	Hits (%)	Mean	Stdev.	Min.	Max.
Time	Research	450 (100%)	22.3	11.9	0	80
	Teaching	450 (100%)	16.1	10.2	0	64
	Others	450 (100%)	12.2	8.7	0	54.6
Age	30 s or younger	42 (9%)	36.9	2.3	25	39
	40 s	214 (47%)	45.0	2.8	40	49
	50 s	155 (35%)	53.7	2.7	50	59
	60 s or older	39 (8%)	62.1	1.5	60	65
Sex	Male/female	410 (91%)	–	–	0	1
Field	Engineering	239 (53%)	–	–	0	1
	Agricultural-life	128 (28%)	–	–	0	1
	Nature	83 (18%)	–	–	0	1
Tenure	Yes	239 (53%)	–	–	0	1
Performance	Projects	450 (100%)	3.2	1.9	0.2	13
	Journal papers	432 (96%)	5.7	5.1	0	40
	Commercialization	126 (29%)	–	–	0	1

academics was 53%. While the ratio of academics who experienced commercialization of their R&D outcome was 28%, 96% of the respondents published at least one journal paper.

Time allocation in our survey means the absolute time (in hours) spent performing research, teaching, and other tasks, of which the sum corresponds to the work time. However, we did not control the variation of work time by respondent. From the survey data, the average work times in hours for research, teaching, and other tasks were 22.3, 16.1 and 12.2 h, respectively. The survey showed that 72% of the respondents experienced changes in time allocation after COVID-19.

Estimation results and discussion

Baseline utility

Table 4 summarizes the MDCEV estimation results for baseline utility. In Table 4, the signs of A_1 and A_3 were negative and positive, respectively. In other words, the baseline utilities of research and other tasks appeared to be lower and higher than the baseline utility for teaching, respectively. Therefore, the academics in our study preferred other tasks, teaching, and then research when other conditions were equivalent.[7] This could reflect academics' obligations of teaching students and performing administrative tasks in addition to research activities. However, such preference varied across independent variables.

[7] The estimation results of Bayesian procedures can be interpreted from a classical as well as a Bayesian perspective (Train, 2009); in this paper we interpret the results from a classical perspective.

Table 4 MDCEV estimation results for baseline utility

Alternative	Variables	Description	Mean	Variance
Research	A_1	Time allocation ASC for research	−0.1453***	1.0623***
	T	Tenure†	0.1362***	1.0275***
	N_{PRJ}	5-year-averaged number of projects (until 2019)	0z.1311***	1.0693***
	N_{PUB}	5-year-averaged number of papers (until 2019)	0.2060***	1.0256***
	B	Commercialization experience†	0.1671***	1.0455***
	COVID	COVID-19†	−0.1994***	1.0312***
Others	A_2	Time allocation ASC for research	0.1130***	1.0700***
	T	Tenure†	0.0911*	1.6511***
	N_{PRJ}	5-year-averaged number of projects (until 2019)	0.3945***	1.0626***
	N_{PUB}	5-year-averaged number of papers (until 2019)	0.1337***	1.0328***
	B	Commercialization experience†	0.2738***	1.0242***
	COVID	COVID-19†	0.3951***	1.0660***

†Dummy variables: 1 with tenure, commercialization experience or after COVID-19; 0 otherwise

***, **, and * correspond to the usual significance levels

Regarding academics' institutional prestige, i.e., tenure

Our estimation results support both propositions 1a and 1b. As shown in Table 4, tenured academics allocated time in stronger preference of research and other tasks to teaching than untenured academics did. Both the coefficients $T \times A_1$ and $T \times A_3$ have positive signs, while the former and latter were statistically significant at 1% and 10% confidence levels, respectively. Our finding appears to be in accordance with that of Fairweather (1993a, 1993b) who investigated the competition between research and teaching when academics allocate their work time. On the one hand, our estimation results agree with the previous studies showing a statistically insignificant effect of institutional benefit such as tenure on decrease in research time (e.g. Milem et al., 2000; Way et al., 2019). On the other hand, academics' preference of time allocation in other tasks to that in teaching was not statistically significant, although its sign was positive, i.e., preferring other tasks. Considering that our survey was carried out for academics in the STEM field, preference of research time allocation suggests their dependence on R&D-project-based-funding to cover the salaries of postdoctoral and graduate students (Woolston, 2020; Science Europe, 2016). In a similar vein, the academics' (although relatively weak) preference of allocating time to other tasks might be closely related to administrative works such as writing research proposals to apply grants for funding, post-award implementation and reporting. In other words, the tenured academics were more inclined to invest their work time primarily in accomplishing the R&D projects with relevant paperwork than the untenured academics were.

Regarding academics' project management

Table 4 also supports both propositions 2a and 2b. Both the coefficients of $N_{\mathrm{PRJ}} \times A_1$ and $N_{\mathrm{PRJ}} \times A_3$ had positive signs and were statistically significant at a confidence level of 1%. The baseline utility coefficient of $N_{\mathrm{PRJ}} \times A_3$ was larger than that of $N_{\mathrm{PRJ}} \times A_1$. This indicates that academics with a larger number of R&D projects were more likely to allocate their work time to other tasks, to research, and then to teaching. The "firefighting" argument (e.g., Bohn, 2000; Repenning, 2001) can explain preferences of academics twofold. On the one hand, the academics' work time allocation to research is expected to decrease as they are involved with more R&D projects. This is because academics need to put more resources into administrative tasks, e.g., writing applications, implementing grants, and finalizing reports (Coviello et al., 2014; Dickinson et al., 2001; Repenning, 2000). On the other hand, a larger number of R&D projects can make it harder for academics to concentrate on each project. Multiple issues can appear simultaneously in multiple projects, and they do not wait, i.e., they need to be solved in a specific time frame. Pushed for time, academics should promptly deal with urgent issues on one project after another. As a result, conducting multiple R&D projects can compromise the quality of the R&D outcome (Jørgensen & Hanssen, 2018), although it can enhance the probability of new R&D grants (e.g. von Hippel's, 2015), i.e., greater funding with a larger number of researchers, technicians or supporting staff (OECD, 2015).

Regarding the academics' research productivity

Table 4 supports both propositions 3a and 3b. Like propositions 2a and 2b, both coefficients of $N_{\mathrm{PUB}} \times A_1$ and $N_{\mathrm{PUB}} \times A_3$ had positive signs and were statistically significant at the 1% confidence level. The former being greater than the latter suggests that academics with more publications were more likely to allocate their work time first to research, then to other tasks, and lastly to teaching. This is in accordance with the literature that found a positive correlation between research productivity and research time (Marsh & Hattie, 2002; Olson & Simmons, 1996). Meanwhile, the academics' work time preference for other tasks over teaching might be because research productivity is closely related to R&D collaborations, which typically require a lot of paperwork, i.e., which is neither research nor teaching.

Regarding commercialization experience

Table 4 supports both propositions 4a and 4b because both positive coefficients of $B \times A_1$ and $B \times A_3$ were significant at the 1% confidence level, and the latter was greater than that the former. This means that academics with commercialization experience have preference for allocating work time first to other tasks, secondly to research and lastly to teaching. Our finding that academics with commercialization preferred research to teaching seems to agree with previous studies. Agrawal (2006) showed that the research time was positively correlated with the chances in which the outcome of R&D was commercialized. Libaers (2012) and Cunningham et al. (2016) reported the effect of technology transfer knowledge sharing (such as attending conferences or participating in consulting services) on successful commercialization. However, previous studies compared neither the effect of time allocation nor the academics' time allocation preferences. The strongest preference of time allocation to other tasks may be due to administrative requirements for collaboration (Devarakonda & Reuer, 2018; Mowery, 1998). Commercialization of academic R&D outcome often requires collaboration between universities and industry (e.g., Couchman & Fulop, 2008; Ven Raesfeld et al., 2012), accompanying statutory and administrative procedures, e.g., for technology transfer. In spite of the legal importance, the cumbersome nature of the procedures can perplex academics. Correspondingly, the academics might prefer to perform "paperworks" first before concentration on research-related issues. As a

Table 5 MDCEV estimation results for satiation parameters

Variables	Description	Mean	Variance
α_1	Satiation parameter for research	0.1354***	0.0141***
α_2	Satiation parameter for teaching	0.0733***	0.0054***
α_3	Satiation parameter for others	0.0570***	0.0042***

***, ** and * correspond to the usual significance levels

result, academics' research time can be compensated by their other task time (Auranen & Nieminen, 2010).

Regarding academics' reaction to the external COVID-19 shock

Contrary to the propositions from 1a to 4b, Table 4 shows that proposition 5a is supported while 5b is rejected. The coefficients of COVID $\times A_1$ and COVID $\times A_3$ are significant at the 1% confidence level, the former and the latter have negative and positive signs, respectively. Considering the sign and magnitude of the coefficients of baseline utility, this means that the academics' preference after COVID-19 was firstly to other tasks, secondly to teaching, and lastly to research. Although Korea experienced no lockdown (You, 2020) in contrast to America or Europe (e.g., Cui et al., 2021; Siegel & Guerrero, 2021), the Korean government administered strong social-distancing measures. As a result, universities introduced stronger access control measures (e.g., anyone should wear a mask to enter a campus) and often forced academics to work at home, especially during school breaks. Access control measures, such as researchers not being able to use the facilities necessary for their studies (e.g., Miki et al., 2020), might have compromised research time.

However, the pandemic hardly eased academics' teaching and other requirements to sustain operation of their institutions (Kruse et al., 2020; Mogro-Wilson et al., 2021). Furthermore, to maintain their research performance, academics needed to continue their research and maintain their laboratories financially with increased time for preparation of research proposals for the next year. Both institutional and individual maintenance concerns could be related to time allocation preferences for other tasks.

The impact of COVID-19 on academics' time allocation to teaching can be understood from a similar perspective. The institutional teaching obligations in Korea have been consistent regardless of governmental social distancing measures: for example, an academic on a typical Korean faculty is required to perform lectures equivalent to at least 6 credits or more. However, social distancing measures forced teaching online (Korea Ministry of Education, 2021; You, 2020), of which preparation and proficiency require significant work time (Ali, 2020; Bolliger & Waslik, 2009; Gloria & Uttal, 2020; Harber & Mills, 2008; Lee & Busch, 2005; Oyarzun et al., 2020; Rapanta et al., 2021 van de Vord & Pogue, 2012;). Institutional requirements and individual efforts for adaptation might be related to the academics' time allocation to preparation of teaching.

Satiation parameters

Table 5 shows the estimation results for the satiation parameters, which indicate academics' diminishing marginal utility for time allocation. The satiation coefficients α_1, α_2 and α_3 (research, teaching and others) were 0.14, 0.073 and 0.057, respectively. All were statistically significant at the 1% confidence level. In Table 5, α_3 pertains the highest satiation, indicating the fastest diminishing of marginal utility for additional allocation of work time. This means that the academics in our study allocated time for other tasks prior to other alternatives. Such allocation preference of time allocation to other tasks does not necessarily mean that academics spend majority of their work time doing tasks other than research and teaching. Rather, it implies that academics are inclined to complete their obligatory tasks so that they can focus on research or teaching.

On the other hand, the marginal utility for additional allocation of research time diminished the slowest because of its lowest satiation. Since the satiation parameters for teaching ($\alpha_2 = 0.073$) and other tasks ($\alpha_3 = 0.057$) were similar to each other compared to that for research ($\alpha_1 = 0.135$), we expect a relatively small contribution of research time allocation to diminishing overall utility. This suggests that, once they have completed their obligatory tasks such as teaching, academics are inclined to allocate their remaining work time to research.

Concluding remarks

Our study results suggest that institutional or governmental policies to promote research time are needed to enhance research, especially in terms of productivity. For example, we confirmed that tenure, as an institutional incentive for academics, can incentivize academics to invest more work time in research. This is because, contrary to the previous findings where tenure was correlated with decreased research time allocation, we found that tenured academics prefer to allocate their work time to research instead of teaching or other tasks. Moreover, our study confirms the virtuous cycle of R&D productivity and research time allocation: we found that academics with larger numbers of R&D projects, journal paper publications, or experience of commercialization tend to allocate work time preferably to research, instead of teaching or other tasks.

Our study also necessitates policies to make up for academics' diminished research time allocation after COVID-19. Although the contribution of research time allocation to diminishing marginal utility (Table 5) was smallest compared to those of teaching and other task time, the coefficients of the baseline utility (Table 4) show that research time allocation was the least preferred when compared to time allocation for teaching or others. Our findings are, to our best knowledge, the first report of the actual loss of preference for research time allocation after COVID-19. This can be explained in two folds. First, after COVID-19, academics had less access to their research resources, e.g. their laboratories and especially graduate students or postdocs, than they did before COVID-19. Although Korea experienced no lockdown in any region throughout the country, strong social distancing and quarantine measures by the Korean government (e.g., Korea Ministry of Education, 2021) might have adversely affected both academics' physical and psychological access to their research resources. Second, institutions such as universities or colleges were concerned about setbacks to their academic calendars due to temporary or permanent loss of human resources and were apt to urge their academics to accomplish tasks related to teaching or administrative works. As a result, research time allocation might be compromised, leading to lower research productivity. Therefore, policy measures are required to address such losses in research time allocation preference. For instance, incentivization of contactless conference platforms such as Zoom, Microsoft Teams and other tasks may be an effective approach considering that collaboration is virtually a must in recent R&D activities

(Devarakonda & Reuer, 2018; Kyvik & Teigen, 1996; Mowery, 1998; Von Raesfeld et al., 2012).

In addition to that, our study necessitates introduction of the policies incentivizing or regulating (especially online) teaching. We suspect academics' propensity toward teaching in this study be essentially due to a lack of supervision of online teaching. Therefore, strengthening evaluation might be a simple and effective means of recovering interests in teaching.

Our study has limitations. From an experimental design viewpoint, academics' choices of time allocations to teaching and others are bounded. Academics in general are obliged to allocate several hours per week to teaching students. Academics are also frequently required to perform administrative work, especially when they are appointed as heads or chairpersons of their departments. As a result, our study does not significantly represent perfectly free academics' preference of work time allocation.

Our study designates all other work time but research and teaching as "other tasks" which are not further classified into, for instance, administrative, external activities and so forth as in previous studies (e.g., Bentley & Kyvik, 2013; Kyvik & Olsen, 2008). This was to minimize the respondents' cognitive burden. Such time for "other tasks" is likely to vary across academics' research fields, ages and other individual characteristics and environments. For example, while relatively young academics (especially in the STEM fields) are likely to allocate time to "other tasks" for administrative works or writing grants or proposals for research projects, relatively old academics are for appointed jobs such as chairpersons or deans and consulting in external committee activities.

Our study assumes the distribution of parameters according to the heterogeneity of academics and estimates the variances of the coefficients of the parameters. Since the estimation results of baseline utility coefficients in Table 4 are characterized as larger variances than their means, the academics in our study appear to have strong heterogeneity, i.e., they do not necessarily represent all of Korea. Similar limitation might apply to the effect of COVID-19 in our study because the pandemic is still ongoing. The survey was conducted in the relatively early stage of the pandemic, Aug 2020, when vaccinations were not available.[8] Therefore, the COVID-19 effect in our study might represent a short-term shock to academics in Korea.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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[8] Vaccination in Korea was started in Feb 2021.

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