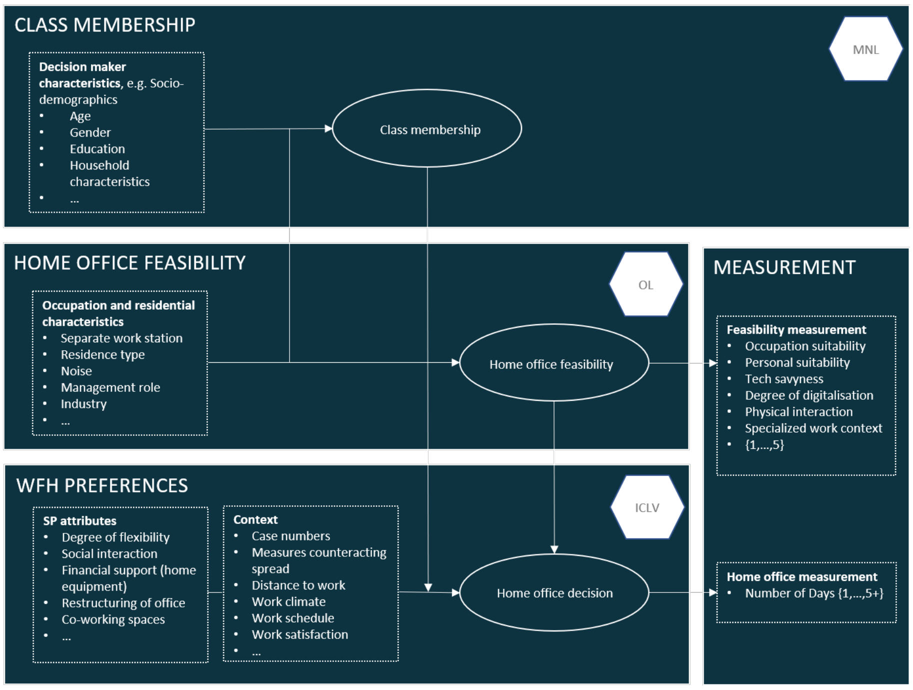

Modeling home office preferences and the implications for transport demand

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Abstract

This paper presents the research plan to elicit home office preferences during the current crisis and beyond as well as resulting transport demand and policy implications. We first identify gaps in the current literature on modeling and understanding work from home (WFH) and discuss in how far our proposal corrects for these limitations. We then introduce the survey instrument consisting of three waves collecting socioeconomic variables, revealed preference (RP) and stated preference (SP) data both in the context of choosing number of days worked from home and the choice of mobility tool ownership (MTO). Whereas the survey instrument presented covers the overarching research intent we focus on WFH in the methodological section. We describe a comprehensive framework for modeling WFH under different hybrid work arrangements and in the context of the pandemic while accounting for home office feasibility and unobserved heterogeneity. The benefits and limitations of our outlined *integrated choice latent variable latent class model* are discussed extensively. A brief overview of the future work and expected impact concludes.

Keywords

Home office, working from home, revealed preferences, integrated choice latent variable, ordered logit, discrete choice, pandemic

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Introduction

With the rise of new information technology the potential to work remotely has been recognized for more than four decades. However, hybrid work arrangements (blending in-office and home office) did not gain traction until recently when the COVID pandemic has forced economies to test work from home (WFH) at a grand scale and fueled a paradigm shift. A possible explanation for the initial resistance could be the fear of productivity loss as well as diminishing engagement and interaction of employees with side effects such as reduced information flow and corporate identity. As new work contracts with potential hybrid work arrangements have yet to be negotiated, it is not clear in what form and to what extent WFH will be relevant in the future. Employees have formed or reevaluated their home office preferences during a crisis when social contacts where considerably reduced. It could very well be that the initial excitement at the beginning of the crisis is as so slowely depleated.

WFH can be seen as a policy lever with the potential to smooth peak traffic volumes with concomitant effects such as reduced greenhouse gas (GHG) emissions. This has considerable implications for transport planners since the capacity of critical infrastructure needs to match peak loads. However, the preferences for WFH in this new era are not well understood. We therefore propose a framework in which we control for home office feasibility, model re-balancing of individuals' mobility tool portfolio as well as gauge resulting transport demand implications at the systemic level where we simulate the interaction between individuals.

This paper lies the ground work to pursue the following research questions: Which jobs are suitable to be performed remotely? What socioeconomic factors explain home office preferences? How can we cluster individuals into homogeneous classes with similar home office preferences? What policies impact the home office choice?

Therefore, the main value proposition is to contribute to a solid understanding of the WFH decision-making process. Only after this achievement can we explain the potential impact and consequences of WFH on different dimensions within our society. In our case, we will leverage the findings in an effort to model shifts in mobility tool ownership (MTO) as well as resulting transport demand implications at the systemic level.

However, the work here presented is merely a think-piece, introducing the reader to the proposed framework of modeling home office preferences. Whereas previous research predominantly looked at home office feasibility of different industries and occupation profiles, personal preferences have largely been neglected. Our research tries to fill this gap by modeling both dimensions simultaneously. Once these two channels are disentangled, we can establish a link to personal characteristics. Who *can* and who *will* be working from home?

Our hypothesis is that individuals can be clustered into homogeneous groups who share similar home office preferences based on their socioeconomic characteristics (class membership). Education, age and household composition are expected to be strong class membership predictors. Home office feasibility is a function of occupation and residential attributes as well as governed by personal characteristics such as psychological traits (e.g. extroversion). Home office feasibility has generic effects (i.e. not class-specific). Feasibility is inherent to an occupation profile, i.e. the degree of digitalization, specialized work context (including equipment) and physical interaction required.

The remaining part is organized as follows: In section 1 we review previous work and identify potential gaps. Section 2 presents the survey instrument with a focus on collecting home office revealed preference (RP) data suitable to estimate our proposed model. Subsequent survey waves are briefly elaborated on to draw the connection to future work. In section 3 we propose the *integrated choice latent variable latent class model* suitable to simultaneously capture home office feasibility as well as preferences while incorporating stated preference (SP) attributes or context variables such as COVID case numbers. Section 4 discusses our propositions while section 5 concludes and outlines the expected impact.

1 Literature review

In parallel to the introduction of new information technology the potential to work remotely has been recognized for more than four decades. However, since the technological boundaries as well as the whole economic and societal environment has changed considerably the findings do most likely not translate to the new age. The curious reader is referred to Beck *et al.* (2020) for an excellent review of this older literature on teleworkability (i.e. WFH) which also recognizes the link from WFH to changes in transport behaviour (see e.g. Jackson and van der Wielen (2002)).

One notable mention from this early work is Brewer and Hensher (2000) for one of the rare stated choice experimental approaches in the context of WFH. They model the interaction between employees and employers and find that employees would like to work more frequently remote but are reticent about how their employers would respond. Tragically, employers were supportive of the idea and revised their position once preferences were revealed. Building on their findings, we could argue that the pandemic resolved this tragedy by enforcing an open debate between employers and employees which fueled the transition.

Another literature is concerned with the WFH feasibility of an occupation, linking work activities and work context metrics to either feasible or infeasible. Dingel and Neiman (2020) construct a binary measure indicating whether or not an occupation can be performed remotely. Their approach only discriminates at the binary level (WFH feasible or not) and does not factor in preferences. The authors find that 37% of the jobs in the United States could be performed entirely remotely and further observe significant variation both across cities and industries. High income jobs are more likely to be suitable for remote work which also links to the finding that low-income countries have lower shares of jobs that can be done at home.

Following the same methodology Gottlieb *et al.* (2021) study how the share of employment that can work from home varies with country income levels. Not surprisingly, the results indicate that richer countries have higher shares, approximately 40% compared to low-income countries where the share is only about 20%. The differences can be explained by larger employment shares in the agricultural sectors as well as more self-employment in less developed countries.

The above presented methodology has one important short-coming: It can not distinguish to what degree an occupation can be performed remotely and thus pictures a very dichotomous world. Further, it focuses on purely technical constraints and abstracts from personal preferences, inferring population shares by aggregating over occupations, i.e. computing the shares of occupations suitable for home office within any given economic industry. The inference drawn is thus fully based on a country's respective economic sector employment shares. The inference drawn at the socioeconomic level merely reflects the prevalence of attributes in any given industry.

Kramer and Kramer (2020) stress that the interplay of occupational and individual characteristics has important research as well as practical implications, when employees' characteristics lead to different productivity levels. In that respect, an important question emerges whether or not employees' with high home office productivity self-select or whether home office provides an opportunity to shirk.

Both researchers and policy makers agree, that hybrid working arrangements can have profound implications for transportation. Hensher *et al.* (2021a) find that reduced commuting activities are associated with higher value of time (VoT) and thus forces policy makers to adjust generalised cost calculations and transport appraisal. However, their findings are very specific to one particular point in time of the COVID pandemic and need yet to be validated and generalised.

Beck and Hensher (2021) suggest that a larger incidence of WFH translates into better transport network performance, especially in larger cities due to reduced traffic congestion and crowding on public transport (PT). Further, as WFH is observed to be evenly spread throughout the week, peak traffic volumes can be reduced. This has considerable implications for transport planners since the capacity of critical infrastructure needs to match peak loads. Yet another important connection can be drawn between WFH and mobility tool ownership as the need to commute decreases: Beck and Hensher argue that car becomes more attractive compared to public transport.

There has been earlier research on WFH that models both the choice and frequency, including Sener and Bhat (2011), Singh *et al.* (2013) and Paleti and Vukovic (2017), each following different modeling strategies. Beck *et al.* (2020) reason that their survey results indicate a sizeable increase in the level of WFH as a proportion of total work in the post pandemic world. From a modeling perspective, they employ an ordered logit choice model. However, no heterogeneity is allowed nor are WFH feasibility considerations incorporated apart from controlling for different industries. Contrasting the findings by Dingel and Neiman (2020), only few occupation classes were found to impact the home office decision significantly.[1] This is a strong indicator that personal preferences and non-technical constraints matter. Meanwhile, personal characteristics had a significant impact on the number of days worked from home which suggests that policy makers should be aware of socioeconomic differences (and social classes) when trying to exploit WFH as a policy lever. Regional differences were also evident with larger cities tending to have a higher probability of WFH, which seems plausible factoring in the different occupation profiles as well as potential preference differences between more rural and urban populations. Importantly, the probability of WFH increases if an individual believes that he is more productive when working from home which hints that employees self-select. The appropriateness of the workplace at home strongly governs home office decisions. The authors mention that there is anecdotal evidence that a growing number of individuals is longing for at least some social interaction in the workplace that is not feasible through digital exchange. Therefore, employers could entice workers back to office by promoting social interaction and aligning presence in the office space. The authors also analyse the influence of WFH on modal dependent commuting activity. In their scenario analysis the number of one-way car commuting trips increases drastically as the population share working 0 days from home increases. On the other hand, demand for public transport trips decreased which could be a direct consequence of present hygiene concerns during the pandemic at that particular stage. The reluctance to return to public transport once safety concerns diminishes is to be explored. Similarly, it is yet to be analysed in how far these shorter term mode choice decisions translate into changes at the longer end, i.e. mobility tool ownership choices.

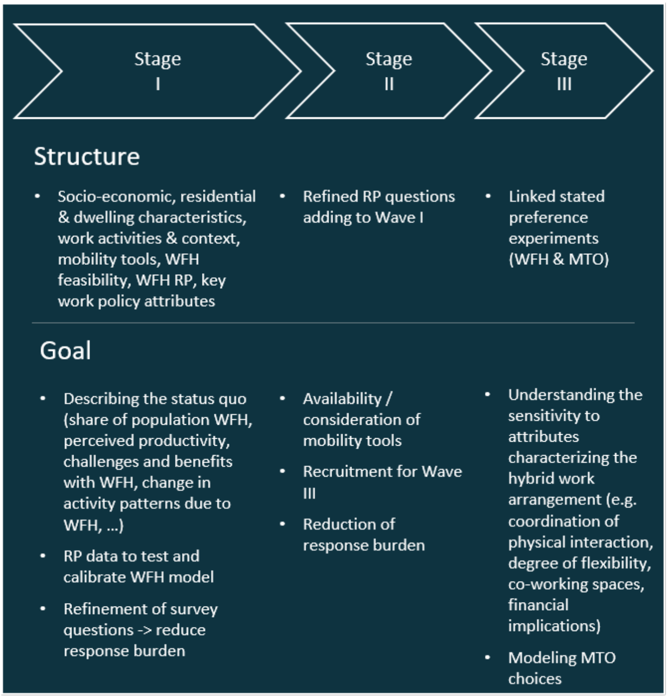
Considerable effort has been devoted to understanding the pandemic's impact both on activity chains as well as mobility patterns (see Beck and Hensher (2020a), Beck and Hensher (2020b), Molloy *et al.* (2021)). Substantial reduction in transport related activities has been observed, weighting heavily on the public transport sector. At the same time a surprisingly large share of the population could shift to WFH (in the case of Australia, 41% of the employed where directed to WFH, with a quarter of the respondents working remotely five days a week) (Beck and Hensher, 2020b). The modal shifts can both be attributed to reduced commuting activities as well as hygiene concerns during the pandemic. However, the effects cannot be disentangled and it remains unsure to what degree they sustain once the pandemic situation becomes more favorable. Not having to commute as well as the freedom of more flexible schedules were the main perceived benefits of working from home (Beck and Hensher, 2020b). Despite potential fatigue to

[1] Again, their findings are very specific to one particular time window during the pandemic and need to be validated. The various constraints enforced by the pandemic makes it difficult to disentangle free choice from forced choice.

work in complete isolation, WFH has been a largely positive experience with the majority of respondents indicating that they would like to work an increased proportion of days from home in the future. As employers' support is high, hybrid working arrangements are likely to stay.

The findings presented suggest that WFH has important implications for transport planners. The share of the population working from home could be substantial especially in developed economies. WFH could alter the perception and value of travel time and thereby force scholars revisiting generalised cost calculations and transport appraisal. WFH has the potential to spread peak traffic volumes both across and within the days and therefore enhance transport network performance. Reduced commuting activity might directly translate into decreased GHG emissions depending on the degree of potential rebound effects. Socioeconomic characteristics play an important role in preference relations and WFH can not be modelled merely from a job description. From the supply side, employers can guide WFH decisions through various policies by promoting social interaction and aligning presence in the office space or subsidize appropriate workplace equipment. At the shorter end, mode choice decisions are impacted by WFH decisions where public transport has large negative elasticities and car has a positive elasticity. A switch from PT to car can be expected. The question remains whether this shift will translate to choices at the longer end, that is changes in mobility tool ownership.

Figure 1: Survey protocol in three stages.



2 Survey instrument

As should be clear from the previous section 1, the preferences for WFH in this new era are not well understood nor have new comprehensive work arrangements crystallized. We therefore propose a framework in which we control for home office feasibility, model rebalancing of individuals' mobility tool portfolio as well as gauge resulting transport demand implications at the systemic level and under different scenarios. As already mentioned, this particular paper focuses on the first aspect, i.e. modeling WFH preferences which form the basis for the subsequent work. We first introduce the overarching data collection strategy consisting of three stages and put emphasis on the architecture of the first stage. In the subsequent methodological section 3 we describe the intended modeling strategy which drives the presented survey instrument and support the relevance of the questions asked.

We propose different survey instruments to collect the data needed to tackle the research questions. To reduce the response burden and logically discriminate the content, we suggest three stages as outlined in figure 1.

2.1 Stage I

Stage I focuses solely on WFH and revealed preference data in an effort to describe and understand the current status quo. The descriptive analysis sheds light on the population share who (at least partially) can work from home, perceived productivity compared to in-office work, challenges and opportunities when working from home, planned changes in mobility tool ownership as well as altered activity patterns when working from home. Further, the longitudinal approach yields three home office choices (number of days WFH per week) during the last two stages of the COVID pandemic[2] as well as in a hypothetical context without any constraints from the employer nor the environment but factoring in the job profile (i.e. the home office feasibility). Meanwhile great emphasis is put on collecting a large set of potentially relevant variables when modeling WFH (see table 2). Most importantly we ask participants to rank different work policy attributes potentially impacting their WFH choices. This question is the foundation for our SP experiments in stage III.

In order to collect data for the home office feasibility component of our model (see section 3) a set of five-point Likert scale indicators is included (with 3 being a neutral option), measuring the home office feasibility. A factor analysis will be conducted revealing the factor structure and loadings. At this stage we include expected signs of the loadings in brackets for each feasibility measurement (fm), where a (+) indicates an increase in home office suitability:

Table 1: Home office feasibility measurement components

Label	**Description**	**Expected loading**
`fm1`	Perceived occupation suitability	+
`fm2`	Perceived personal suitability	+
`fm3`	Personal technical savyness	+
`fm4`	Job's degree of digitalisation	+
`fm5`	Job requires physical interaction	−
`fm6`	Job requires specialized work context	−

7000 participant spread evenly across the German-speaking part of Switzerland are contacted and no incentives are paid at this stage. The invited participants match the joint distribution of targeted variables from the Swiss microcensus.

[2] i.e. numer of days worked from home during the Omicron stage with compulsory home office as well as number of days worked from home during the time window since restrictions have been abolished

Table 2: Topics and attributes included in stage I

Topic	**Attributes**
socioeconomic	age, gender, education, ...
residential & dwelling	address, apartment type, ...
work station	separate room for home office, external monitor, ergonomic chair, ...
employment	employment status, contracted hours, work satisfaction, number of subordinates, ...
mobility	mobility tools, subscriptions, commute mode, ...
home office feasibility	degree of digitalisation, physical interaction required, ...
home office choices	number of days WFH per week, perceived productivity, challenges, ...
work policies	ranked ordering of different work policy attributes
personal characteristics	feeling lonely, enough spare time, extroverted, ...

2.2 Stage II

In stage II we will revise our questionnaire based on the insights from modeling WFH with the data collected during the first stage. Further, we collect all the data required to design the SP experiments conducted during stage III. This includes availability considerations with regards to mobility tool ownership as well as employment status and home office eligibility. The canton and city of Zurich serve as a case study to provide policy implications and therefore stage II also maps commuting streams into the city of Zurich.

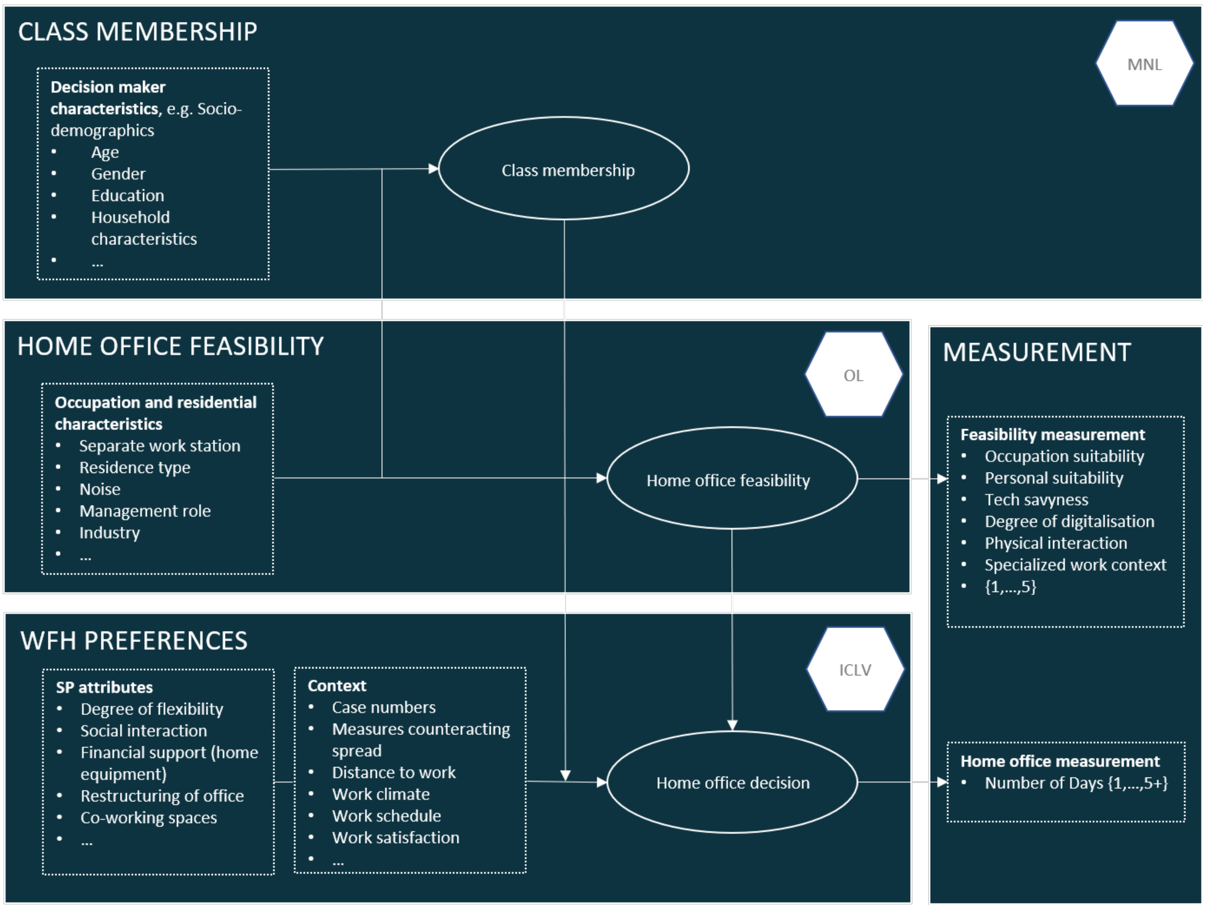
2150 participants will be recruited in the German-speaking part of Switzerland, oversampling the canton and city of Zurich. Respondents from stage I are invited to participate in subsequent stages, if they approved the approach in stage I. The federal statistical office as well as the statistical office of the canton of Zurich are contacted to provide the addresses. An incentive of 20 Swiss francs is paid on completion of stage III.

2.3 Stage III

Stage III comprises a linked SP experiment where respondents are asked to select the number of days and weekdays to be worked from home, as well as their preferred mobility tool ownership given the scenarios we carefully design. The attributes of the WFH SP characterize a hypothetical hybrid work arrangement, with meaningful trade-offs imposed as revealed during the first stage. The MTO SP puts emphasis on the trade-off between

PT season ticket and car ownership as well as non-motorized individual vehicles (i.e. bikes and E-bikes). Among others, different power trains are considered for car. We either follow a stated adaptation (SA) approach or a more classical SP pivot design: In the SA, individuals can choose the portfolio of mobility tools, their characteristics and the annual mileage while being informed about the implied costs. They can readjust their choices until they are satisfied. In the more classic SP design, static mobility tool bundles are presented as alternatives while each bundle is further characterized by pre-selected attributes.

Figure 2: Latent class ordered logit modeling framework with a latent home office feasibility component.



3 Methodology

Whereas the previous section 2 reflected the survey instruments for the overarching research project, we focus on analysing the data collected during wave I in the remainder of the paper.

As discussed in section 1 the combination of home office feasibility and personal preferences has not yet been scrutinized. Therefore we propose a framework which accounts for this shortcoming. Specifically, we plan to employ an *ordered logit latent variable latent class model*, where home office feasibility is incorporated via a latent variable. The statistical model is known as *integrated choice latent variable model* (ICLV), as described in Walker and Ben-Akiva (2002).

The structural model inspired by Ghasri and Vij (2021) is visualised in figure 2 and comprises three parts:

- The class membership model
- The home office feasibility model
- The home office decision model

Each of the three sub-models will be characterized in turn.

3.1 The class membership model

A latent class model is used to account for effect heterogeneity while providing a very elegant way of interpreting the composition of the different classes. A class is a collection of socioeconomic attributes featuring a similar preference relation. That is some utility weights will be class-specific. The class membership model is a simple multinomial logit model where the total number of classes S will be determined in the model-building process based on statistical measures of fit.

$$P(q_{ns} = 1) = \frac{\exp(\gamma_s Z_n)}{\sum_{s=1}^{S} \exp(\gamma_s Z_n)} \tag{1}$$

q_{ns} is a binary variable indicating whether individual n belongs to class s. Z_n is a vector of socioeconomic characteristics for individual n. γ_s is a vector of class-specific parameters indicating the sensitivity to individual n's characteristics.

3.2 The home office feasibility model

We think of home office feasibility as a continuous (bounded) latent variable (LV). The LV is defined in the structural model by measurable socioeconomic characteristics, whereby the measurement component links the LV with indicators that are assumed to be affected by the latent construct (Schmid, 2019). The structural equation for home office feasibility is a linear function of observed socioeconomic characteristics Z_n as well as as occupation

O_n and residential characteristics R_n.

$$
\begin{aligned}
LV_n &= \zeta Z_n + \phi O_n + \rho R_n + \eta_n \\
\eta_n &\sim N(0, \sigma^2_{LV})
\end{aligned}
\tag{2}
$$

where η_n captures some unobserved heterogeneity in the structural component and ζ, ϕ and ρ are the parameter vectors to be estimated.

The latent variable measurement equations with responses to the home office suitability questions (Likert scale indicators) $I_{w,n}$ with $w \in \{\text{fm1, fm2, ... fm6}\}$ (see table 1) are given by

$$
\begin{aligned}
I_{w,n} &= \bar{I}_w + \tau_w LV_n + \upsilon_{w,n} \\
\upsilon_{w,n} &\sim N(0, \sigma^2_{I_w})
\end{aligned}
\tag{3}
$$

where $\bar{I}_w$ are the mean ratings of the five-point Likert scales of each item w and $\upsilon_{w,n}$ corresponding to the error distribution. τ_w is the vector to be estimated, linking the latent variable to the measurement. In principal, the Likert scales would imply another ordered logit model when deriving the likelihood. However, as has been shown by Schmid (2019) a linear representation produces more stable estimates and reduces model complexity while yielding similar results.

3.3 The home office decision model

The home office decision model is the structural model that nests the two previously described models. The individuals choose the number of days worked from home during a week given the scenario prescribed. The likelihood function will reflect the ordered choice nature of the choice task. In the case of RP data collected during wave I, these are context variables, such as COVID case numbers, distance to work, work climate, work schedule, etc. whereas at later stages these are enriched by SP attributes characterizing the hybrid work arrangement. These scenario / context variables are denoted by $X_{n,t}$. Importantly, home office feasibility LV is not class-specific but directly impacts the home office decision (generic effect). The conditional (conditional on class-membership s) utility relation reads

$$u_{n,t|s} = \beta_s X_{n,t} + \kappa_s O_n + \lambda_s R_n + \theta LV_n + \varepsilon_{n,t|s} \tag{4}$$

Whereas socioeconomic variables can either act via class-membership or home office feasibiltiy, occupation and residential characteristics either act via home office feasibility or directly influence utility.

4 Discussion

As a first remark our ex ante model specification might change considerably during the modeling process. Our model building strategy first abstracts from latent classes and incorporates heterogeneity either by specifying model parameters a function of socioeconomic factors or by mixing distributions. However, we believe the interpretation of the latent classes to be very valuable for policy discussions, where one has to understand the policy impact on different social groups.

Further we will first model the home office feasibility model as linear equation (interpreting the Likert scale as continuous and unbounded) before employing a more complex ordered logit approach. A sequential model estimation is considered first before modeling the system simultaneously.

To reduce the response burden of wave I, detailed psychological measures (e.g. the big 5 personality traits) can only loosely be approximated with our questions. Risk aversion metrics are not included and therefore we can't control for fear of transmission during the COVID phases. However, as long as risk aversion is evenly represented across different social groups, our analysis should not be biased.

The phase where mandatory home office was imposed (one data point of RP WFH choices) is expected to strongly discriminate between the population who was able to perform at least some of their work from home and those that were not. We have to test whether we will be able to control for that enforced home office, i.e. in how far the estimates differ when the data points are excluded.

The inclusion of occupation and residential characteristics in equation 4 has to be assessed. In principle, a separate work station or a bigger house could very well increase the benefits of WFH (i.e. increase the utility) whereas it could also be hypothesised to only impact choices via home office feasibility.

One of the benefits of our proposed framework is the ability to estimate the model on pooled SP / RP data where the only distinction is drawn in the specification of the variable $X_{n,t}$ in equation 4. This allows us to calibrate the SP model while at the same time enriches the RP model with more meaningful and non-observable trade-offs.

To give a brief outlook, we suggest a two stage linked SP experiment where we try to link number of days worked from home to mobility tool ownership choices. This will inform policy makers about expected long-term modal shifts as well as implications for public transport providers. Respondents will first choose the number of days worked from home given the proposed scenario. Their choice is then directly carried forward to the mobility tool ownership experiment. This has the benefit of a natural causal direction from WFH choices to mobility tool ownership. Nevertheless, we might expect reverse causality which would suggest a simultaneous estimation of the two. However, understanding such a choice context becomes very difficult, since the respondent needs to grasp both the WFH and MTO scenario at the same time (explosion of SP attribute space).

A further complication arises in the modeling strategy, combining the WFH and MTO model. We either estimate nested models (i.e. a simultaneous estimation) or follow an approach similar to Beck *et al.* (2020) or Hensher *et al.* (2021b) where we incorporate the predicted choice probabilities of the WFH model in the latter one, correcting for the covariance error structure at this second stage (Murphy and Topel, 2002).

5 Conclusion and expected impact

WFH can be seen as a policy lever to smooth peak traffic loads and reduce mileage travelled. To understand the overall demand implications we propose a WFH discrete choice model, accounting for home office feasibility as well as individual preferences. The model allows us to elicit who *can* and who *will* be working from home given different hybrid work arrangements. Testing the framework on RP data helps us to understand the status quo as well as allows for refinements of both the survey instrument and modeling framework. Further, a model calibration of the hypothetical SP context can be achieved. Looking ahead, the WFH model will be linked to mobility tool portfolio choices (via another SP experiment) followed by a mode choice SP. This yields the building blocks for our MATSim simulation implementation whereby we can gauge the resulting demand implications at a systemic level. The research will inform policy makers about the expected new transport equilibrium and in how far WFH serves as a tool to break peak traffic volumes as well as tackle concomitant effects such as GHG emissions. This has to be seen in the perspective of potential rebound effects caused by altered activity chains.

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