Multimodality in the Swiss New Normal (SNN)

Future Mobility Research Program

Report

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Publication date:
2024-05

Permanent link:
https://doi.org/10.3929/ethz-b-000674149

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Project report **March 2024**

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March 2024

Abstract

This report investigates mobility behavior in a new normal, characterized by a large population share adopting home office. A representative sample of the German-speaking part of Switzerland was recruited to elicit home office preferences and implications for mobility tool ownership. The models are then integrated into the travel demand synthesis pipeline (*eqasim*) of the multi-agent transport simulator (*MATSim*) for the case of Zurich. We designed strategies that represent different realistic ways agents can adapt their behavior when they are working from home. The strategies are simulated on an average weekday and Friday as the latter has empirically much higher home office shares. We find that a substantial reduction in the number of trips is achieved, especially during peak hours, while the mode shares remain stable. Home office ultimately seems to improve traffic conditions for motorists suggesting that congestion on major commuting axes could be substantially reduced. We further find strong evidence against off-setting rebound effects with a reduced number of trips and traveled distance across all modes. Home office therefore can be an effective policy lever to improve network conditions and attenuate any negative traffic-induced externality. Further, it does not distort mode preferences and therefore, the infrastructure does not need to be readjusted.

Keywords

Home office, telework, microsimulation, mobility behavior, transport system, MATSim

Suggested Citation

Heimgartner, D., A. Sallard, M. Balac and K.W. Axhausen (2024) *Multimodality in the Swiss New Normal (SNN)*, Future Mobility Research Program, CSFM, ETH Zurich, Zurich.

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März 2024

Zusammenfassung

Dieser Bericht untersucht das Mobilitätsverhalten in einem neuen Normalzustand, welcher durch einen grossen Anteil der Bevölkerung gekennzeichnet ist, der im Home Office arbeitet. Eine repräsentative Stichprobe der deutsch-sprachigen Schweiz wurde rekrutiert, um Präferenzen für das Home Office und Auswirkungen auf den Besitz von Mobilitätswerkzeugen zu ermitteln. Die Modelle wurden anschliessend in die Simulationssoftware *MATSim* integriert, indem eine synthetische Population für Zürich generiert wurde. Wir haben verschiedene Strategien entwickelt, um die potentiell alternativen Aktivitätenketten der Home Office Bevölkerung abzubilden. Die Strategien werden an einem durchschnittlichen Wochentag und Freitag simuliert, wobei letzterer empirisch einen deutlich höheren Anteil an Home Office aufweist und daher einen Extremfall darstellt. Wir zeigen, dass eine deutliche Reduzierung der Anzahl von Fahrten erreicht wird, insbesondere während den Stosszeiten. Die Verkehrsmittelwahl bleibt hingegen stabil. Das Home Office scheint letztendlich die Verkehrsbedingungen für Autofahrer zu verbessern, was darauf hindeutet, dass Staus auf wichtigen Pendelachsen erheblich reduziert werden könnten. Induzierte Nachfrage-Effekte, welche eingesparte Pendlerwege ausgleichen oder sogar überkompensieren sind sehr unwahrscheinlich: Die Simulationen ergeben eine reduzierte Anzahl von Fahrten und zurückgelegte Entfernungen über alle Verkehrsmittel. Home Office könnte daher ein wirksamer politischer Hebel sein, um Netzwerkbedingungen zu verbessern und negative verkehrsbedingte Externalitäten zu mildern. Darüber hinaus werden Verkehrsmittelanteile nicht verzerrt und die Infrastruktur muss folglich nicht neu ausgerichtet werden.

Schlagworte

Home Office, Mikrosimulation, Verkehrsverhalten, Verkehrssystem, MATSim

Zitierungsvorschlag

Heimgartner, D., A. Sallard, M. Balac and K.W. Axhausen (2024) *Multimodality in the Swiss New Normal (SNN)*, Future Mobility Research Program, CSFM, ETH Zurich, Zurich.

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Executive summary

This report investigates mobility behavior in a new normal, characterized by a large population share adopting home office. In this environment, transport demand might be affected via several channels. The most obvious one is teleworkers not commuting. However, more indirect effects might play a role too. We hypothesize that the main leverage influencing the new transport equilibrium is threefold: First, the population share having access to hybrid work forms and wanting to work remotely. Second, the home office population reconsiders mobility tool ownership and third, they might have different activity patterns than the regular workforce. We generate a synthetic population with calibrated work from home (WFH) shares, mobility tool ownership (MTO) shares and execute different alternative activity plans in the Multi-agent transport simulator (MATSim) to investigate network conditions in this new normal.

Literature that takes such a holistic perspective on understanding home office consequences for the transport system is sparse and contradictory. For example, it is debated whether or not telework decreases or increases trip frequency as rebound effects (offsetting commuting trips) potentially exist. Meanwhile, the home office adoption and situation more generally is different from country to country and largely depends on its economic structure. Therefore the external validity of previous results is questionable and a detailed case study is worth-while. We do so in a buffered-area around the city of Zurich allowing for in-bound commutes.

Evaluating the impacts of home-office on urban transportation can help assess the potential environmental benefits, such as reduced emissions and improved air quality, induced by the potential reduction of travel time and shift towards more sustainable transport modes.

As part of this work, a unique dataset was collected, tailored to elicit WFH preferences and resulting changes in MTO. The addresses were drawn from a stratified sample of the German-speaking part of Switzerland, obtained from the address registry of the Federal Statistical Office. Respondents were invited to answer an online questionnaire asking about socioeconomic characteristics, the residential environment, home office situation, as well as work-related and mobility-related topics. Subsequently, people in the workforce and eligible to work from home partially, were invited for a WFH and MTO stated preference (SP) survey.

We observed a shift from very high home office frequencies (during the pandemic) to two or three days (after the pandemic). Meanwhile, home office access remains at high levels (47%) suggesting that employees who have gained access to the new work form during the pandemic are still (partially) working from home. From an employee preference perspective, the current situation does not constitute an equilibrium: A large portion would like to increase WFH frequencies, in particular, the population currently not having access (potentially reducing the share not working from home to roughly 30%).

Generally, Mondays and Fridays are the preferred weekdays to WFH. We computed the population share working from home on any given weekday and under alternative frequency scenarios. The previously alluded potential shift yet to come has considerable leverage, increasing the home office share across weekdays substantially. Friday is the upper bound with almost half of the workforce staying at home. Tuesdays and Thursdays still show the lowest shares and transport infrastructure would need to account for these loads. The gap between the days widens under the free-choice scenario with potentially very different network loads over the days. Therefore, Fridays and Tuesdays to Thursdays should be analyzed separately, when looking at the impact of home office on transport demand. Additionally, the difference between the free-choice and observed frequencies suggests, that there is still a potential for further change. We should therefore try to understand, why this difference exists and under what circumstances it would diminish.

In this regard, we investigated how far hybrid work arrangement characteristics can incentivize deviation from the unconstrained free choice. We find that salary adjustments, the option to work from anywhere, full employer participation in additional cost and desk sharing in the office all increase home office frequencies. A salary increase of 10% (on home office days) and the possibility to work from anywhere show the strongest effects and are similar in magnitude (around 0.2 d/week). Coordination of office presence decreases the home office frequency. However, these effects (while significant) are not substantial. In particular, they can not explain the observed difference between currently observed frequencies and the free choice which is around 0.6 d/week. A more probable explanation is that employers and employees negotiate the maximum number of days and employers generally prefer more office presence. While we do not pursue this avenue, it would be important to understand the employers' preferences and the negotiation process.

The home office model for the MATSim integration was solely based on revealed preference (RP) data. The model features a Heckman-type selection mechanism controlling for home office access. Binary probit models were estimated on pooled RP-SP data deriving home office sensitivities from the SP data. These implied sensitivities are 3.1 percentage points (pp) and 4.7 pp for the marginal home office day and the national season ticket (GA) and regional subscriptions respectively. In other words, if aggregate home office supply increases by one full day, PT subscription shares drop by these numbers. No significant effects were found for the other modes.

Those findings needed to be generalized to a full-size population, and translated in terms of travel behavior (different activities, different use of transport modes, ...) in order to evaluate the impacts home office may have on the transport system. For this purpose the *eqasim* pipeline was carefully extended, finally enriching the synthetic population with home office plans, a new set of mobility tools owned and context-specific travel plans.

In particular, we proposed four heuristic strategies to model activity plans of the home office population: One of them is based on the TimeUse+ survey (a unique App-based travel diary fielded after the COVID-pandemic) and the other three are adaptations of the mobility data from the microcensus. Two dimensions were investigated: changes in the performed *activities* and changes in activity *locations*. Our approach is likely to cover a wide range of real-life situations with the status quo likely lying somewhere "between" the envisioned scenarios. While we only executed two of these strategies (as well as the baseline without home office), the transport implications are almost identical across the scenarios. As already mentioned, home office patterns can be expected to be different for the average weekday and Monday/Friday, where Friday constitutes the edge case with the highest home office share. Therefore, the modeled strategies are executed for an average weekday and a Friday separately.

Our calibrated MATSim model matches the observed home office and mode shares very well. Around 70% of the employed workforce could in principle work from home which further highlights that Zurich is an interesting use case.

The analysis part of the report compared the variation of key mobility indicators between the scenarios. While the chosen strategy seems to have minimal to negligible effect on the results, the simulated day has a major impact. We show that a substantial reduction in the number of trips is achieved, especially during peak hours, while the mode share remains stable, only showing a minor reduction in the share of public transport at the benefit of active modes. Home office ultimately seems to improve traffic conditions for motorists with an increase in the average observed speeds. This indicates that congestion could be substantially reduced on the major commuting axes.

Most importantly, the analysis yields strong evidence that the possible rebound effects do not offset reduced commuting activities by a wide margin. The number of trips and traveled distance are reduced across all modes. Home office therefore can be an effective policy lever to improve network conditions and attenuate any negative traffic-induced externality (such as greenhouse gas emissions). Further, it does not distort mode preferences and therefore, the infrastructure does not need to be readjusted. This underscores the desirability of home office from a social welfare perspective.

While the evidence for home office and productivity implications is mixed, the foregone negative externalities might offset potential productivity losses. The analysis suggests that there still is a large leeway and employees would like to work remotely more often. Therefore policymakers could think about incentivising home office to improve overall welfare.

Kurzfassung

Dieser Bericht untersucht das Mobilitätsverhalten im neuen Normalzustand, welcher durch einen grossen Bevölkerungsanteil gekennzeichnet ist, der im Homeoffice arbeitet. In diesem Umfeld könnte die Verkehrsnachfrage durch mehrere Kanäle beeinflusst werden. Das Wegfallen eines Grossteils der Pendlerwege scheint einer der offensichtlichsten Kanäle. Jedoch könnten auch indirekte Effekte eine Rolle spielen, insbesondere durch die neu gewonnene Flexibilität in der Zeit- und Arbeitseinteilung. Die Analyse identifiziert drei Hauptfaktoren, deren nähere Ergründung erforderlich ist, um das neue Verkehrsgleichgewicht zu untersuchen: Erstens, der Bevölkerungsanteil, der Zugang zu hybriden Arbeitsformen hat und diese auch nutzen möchte. Zweitens, mögliche Anpassungen im Mobilitätswerkzeugbesitz aufgrund der sich ändernden Rahmenbedingungen, und drittens, alternative Aktivitätenketten der Homeoffice-Bevölkerung. Wir generieren eine synthetische Bevölkerung mit kalibrierten Homeoffice-Anteilen, sowie realistischen Besitzanteilen der jeweiligen Mobilitätswerkzeuge. Anschliessend führen wir die identifizierten Aktivitätenketten der Bevölkerung aus, um mittels der Simulationssoftware MATSim die resultierenden Netzwerkbedingungen im neuen Normalzustand zu untersuchen.

Die Analyse trägt zur spärlichen Literatur bei, welche einen gesamtheitlichen, systemischen Ansatz verfolgt, um den Einfluss von Homeoffice auf die Verkehrsnachfrage zu untersuchen. Zudem existiert kein Konsens, ob Homeoffice nun zu Mehrverkehr führt oder nicht. Das Narrativ des sogenannten Rebound-Effekts hält sich hartnäckig. Dieses besagt, dass sich die Homeoffice-Population aufgrund der angesprochenen Flexibilität freier und mehr bewegt und die wegfallenden Pendlerwege überkompensiert. Darüber hinaus zeigt sich, dass verschiedene Länder aufgrund ihrer Wirtschaftsstruktur stark unterschiedliche Homeoffice-Anteile und Potentiale aufweisen. Daher ist die externe Validität bestehender Studien und Resultate kritisch zu betrachten. Eine detaillierte Fallstudie ist folglich notwendig. Die Analyse fokussiert sich auf den Grossraum Zürich inklusive Pendleranteile von ausserhalb.

Aus verkehrsplanerischer Perspektive ist es wichtig das neue Verkehrsgleichgewicht zu verstehen, um die bestehende Verkehrsinfrastruktur zu evaluieren bzw. für deren Neuausrichtung zu planen. Ebenfalls gilt es, Auswirkungen auf die Verkehrsnachfrage zu quantifizieren, um die positiven/negativen Effekte abwägen zu können. Wieviel wird mehr oder weniger gereist? Gibt es eine stärkere Nachfrage für bestimmte Verkehrsmittel? Was sind resultierende Umwelteffekte? Wie verteilt sich die Verkehrsnachfrage über den Tag oder die Woche?

Im Rahmen dieser Arbeit wurde ein einzigartiger Datensatz generiert, der darauf abzielt, die Präferenzen für Homeoffice und die daraus resultierenden Änderungen im Mobilitätswerkzeugbesitz zu ermitteln. Die Adressen wurden aus einer geschichteten Stichprobe der deutschsprachigen Schweiz aus dem Register des Bundesamtes für Statistik gezogen. Die Befragten wurden eingeladen, an einer Online-Umfrage teilzunehmen, die Fragen zu sozioökonomischen Merkmalen, dem Wohnumfeld, der Homeoffice Situation, sowie arbeits- und mobilitätsbezogenen Themen beinhaltete. Anschliessend wurden Personen, die erwerbstätig sind und teilweise von zu Hause aus arbeiten können, zu zwei Stated Preference (SP) Experimenten eingeladen. Einerseits wurde untersucht, inwiefern arbeitsvertragliche Rahmenbedingungen die Homeoffice-Frequenz beeinflussen können, andererseits den Einfluss von Homeoffice auf den Verkehrswekzeugbesitz.

Die erhobenen Daten erlauben uns ebenfalls, die Pandemie-getriebenen Veränderungen in den Kontext zu setzen. So beobachten wir eine Verlagerung von sehr hohen Homeoffice-Frequenzen während der Pandemie, zu zwei bis drei Tagen. Jedoch ist auffallend, dass der Homeoffice Zugang mit rund 47% weiterhin hoch bleibt und sich deutlich von der vor-pandemischen Situation unterscheidet. Währenddessen äussern Erwerbstätige den Wunsch, noch mehr von zu Hause aus arbeiten zu dürfen. Das Arbeitsmarktgleichgewicht scheint folglich fragil: Insbesondere der Bevölkerungsanteil, welcher Momentan noch keinen Zugang zu Homeoffice hat, möchte dies ändern, wodurch sich der Homeoffice Anteil gar bis auf 70% erweitern könnte.

Montage und Freitage sind die bevorzugten Wochentage, um von zu Hause aus zu arbeiten. Wir berechneten den Bevölkerungsanteil, welcher an einem beliebigen Wochentag im Homeoffice verweilt: Der zuvor erwähnte Überhang (freie Präferenz der Arbeitnehmer) hat einen substantiellen Einfluss. Freitage stellen den Extremfall dar, mit beinahe der Hälfte der Bevölkerung, welche im Homeoffice arbeitet. Dienstage und Donnerstage weisen weiterhin die niedrigsten Anteile auf und die Verkehrsinfrastruktur müsste diesen Netzwerkbedingungen Rechnung tragen. Der Unterschied zwischen den Wochentagen spitzt sich also weiter zu, was zu sehr unterschiedlichen Verkehrsbedingungen führen könnte. Daher empfehlen wir, dass die Wochenrandtage und -mitteltage separat analysiert werden. Darüber hinaus stellt sich die Frage, was die Diskrepanz zwischen den aktuellen Homeoffice Frequenzen und dem freien Homeoffice Angebot (der Arbeitnehmenden) erklärt.

In dieser Hinsicht untersuchten wir, inwiefern die Form der hybriden Arbeitsbedingungen und Vereinbarungen Anreize schaffen könnte, um eine Abweichung von der freien Wahl zu motivieren. Wir finden klare Präferenzen für gewisse Arbeitsbedingungen und ebenfalls das Potential, dass diese die Frequenzwahl beeinflussen können. Jedoch sind die resultierenden

Sensitivitäten gering und können die obig erwähnte Diskrepanz nicht erklären.

In der Konsequenz basiert das Homeoffice Modell ausschliesslich auf Revealed Preference (RP) Daten. Das Modell beinhaltet einen Heckman Selektionsmechanismus, welcher sowohl den Homeoffice Zugang als auch die Frequenzwahl gleichzeitig abbildet. Für den Verkehrswerkzeugbesitz schätzten wir binäre Probitmodelle, basierend auf kombinierten RP-SP Daten. Die implizierten Sensitivitäten sind 3.1 Prozentpunkte (pp) und 4.7 pp für das GA und Regional Abo respektive, und den marginalen Homeoffice Tag. In anderen Worten, steigt die aggregierte Homeoffice Frequenz um einen vollen Tag (was sehr hoch wäre), würde die Nachfrage nach den ÖV-Pässen um die erwähnten Zahlen sinken. Die weiteren Verkehrswerkzeuge (Halb-Tax, Auto, Autoleih/Carsharing und Fahrrad) zeigen keine signifikanten Effekte.

Diese Ergebnisse mussten nun für die vollständige, synthetische Population verallgemeinert werden und im Hinblick auf das Reiseverhalten (unterschiedliche Aktivitätenketten, unterschiedliche Verwendung der Verkehrsmittel, etc.) übersetzt werden, um die Auswirkungen des Homeoffice auf die Verkehrsnachfrage zu bewerten. Zu diesem Zweck wurde die *eqasim*-Pipeline erweitert, wodurch die Bevölkerung schliesslich um Homeoffice Pläne, einem neuen Satz von Mobilitätswerkzeugen und kontextspezifischen Reisepläne ergänzt wurde.

In diesem Sinne schlugen wir vier heuristische Strategien vor, um die Reisepläne der Homeoffice Bevölkerung abzubilden: Eine dieser Strategien basiert auf den TimeUse+ Daten (ein einzigartiges App-basiertes Reisetagebuch, durchgeführt nach der COVID-Pandemie). Die weiteren Strategien beruhen auf Anpassungen der Mobilitätsdaten des Mikrozensus für Mobilität und Verkehr. Insbesondere wurden zwei Dimensionen berücksichtigt: Erstens, Anpassungen der *Aktivitäten* als solche und zweitens, Anpassungen des *Zielortes*, wo diese Aktivitäten durchgeführt werden. Unser Ansatz deckt eine Fülle an möglichen Situationen und der Status quo liegt irgendwo zwischen diesen Szenarien. Zwei dieser Strategien (und das Referenzszenario ohne Homeoffice) wurden in MATSim implementiert und die Verkehrsgleichgewichte zeigten sich erstaunlich robust. Die Strategien wurden sowohl für einen durchschnittlichen Wochentag als auch für Freitag separat evaluiert.

Unser kalibriertes MATSim Modell bildet die beobachteten Homeoffice-Anteile und Verkehrsmittelanteile sehr präzise ab. Um die 70% der Arbeitskräfte könnten prinzipiell von zu Hause aus arbeiten, was weiter unterstreicht, dass Zürich eine relevante Fallstudie darstellt.

Die Hauptanalyse des Berichts vergleicht verschiedene Mobilitätsindikatoren zwischen den beiden Szenarien und der Referenz (ohne Homeoffice). Wie bereits erwähnt, sind die Resultate nicht getrieben von den heuristischen Strategien (um Aktivitätenpläne zu identifizieren). Die simulierten Wochentage hingegen unterscheiden sich stark. Die Analyse zeigt eine erhebliche Reduktion bezüglich Anzahl Reisen, insbesondere während den Spitzenzeiten. Die Verkehrsanteile bleiben jedoch stabil. Lediglich der öffentliche Verkehr ist leicht weniger nachgefragt und wir durch aktive Modi substituiert. Nicht zuletzt scheint Homeoffice die Verkehrsbedingungen für den motorisierten Individualverkehr zu verbessern, mit erhöhten durchschnittlichen Reisegeschwindigkeiten. Dies legt nahe, dass der Verkehrsfluss auf den Hauptachsen verbessert werden kann.

Unsere Studie unterstreicht, dass zumindest in der betrachteten Grossregion keine Rebound-Effekte zu erwarten sind: Die eingesparten Pendlerwege werden nicht vollständig kompensiert. Die Etappenanzahl und die zurückgelegte Gesamtdistanz verkleinerten sich für jedes einzelne Verkehrsmittel. Homeoffice kann daher als Instrument betrachtet werden, um negative verkehrsbedingte Externalitäten zu mindern. Des Weiteren werden Verkehrsmittelanteile nicht verzerrt und die Ausrichtung der Verkehrsinfrastruktur muss daher nicht direkt in Frage gestellt werden. Aus einer Verkehrsperspektive scheint Homeoffice die soziale Wohlfahrt zu steigern.

Von der Arbeitgeberperspektive stellt sich die Frage, ob und ab welchem Masse Homeoffice produktivitätssteigernd bzw. -mindernd wirkt. Die Evidenz diesbezüglich ist gemischt. Jedoch haben wir in der Studie festgestellt, dass die gewünschte Homeoffice Frequenz von der Arbeitgeberseite eingeschränkt wird und dementsprechend das volle Potential noch nicht ausgeschöpft ist. Politische Entscheidungsträger könnten sich überlegen, Rahmenbedingungen zu schaffen, welche Homeoffice begünstigen und Arbeitgeber ermutigt, hybride Arbeitsformen zu unterstützen. Die Koordination über die Unternehmensgrenze hinaus würde ebenfalls zu einer gleichmässigeren Verteilung der positiven Effekte über die Wochentage beitragen.

1 Introduction

The information and communication technologies (ICT) revolution was the first enabler of remote work. Together with the service industry becoming more important as part of the economic transformation and in line with the digital transformation, telework was on a steady growth path. However, the COVID-pandemic further accelerated the advent of telework, quadrupling the home office share in only a few years (Barrero *et al.*, 2023). As economies around the globe successfully tested hybrid work forms, momentum shifted from the employers to employees, now demanding remote work to be an integral work policy.

Before the pandemic, working from home was the exception rather than the rule. "Shirking from home" was stigmatized and perceived to be bad for career advancements and therefore workers were afraid to postulate their desire (Brewer and Hensher, 2000). In fact, Mokhtarian and Salomon (1996) found that telework was a *preferred impossible* alternative for a large share of workers. In that sense, the pandemic helped break the stigma of working from home and relaxed some of the constraints, making it a preferred possible scenario for many.

Remote work grew from roughly 7% participation in the US and 5% across Europe to about 62% and 37% respectively, through the first waves of the pandemic in 2020 and 2021 (see DeSilver 2020; Eurostat 2020; Gallup 2020; Eurofound 2020).

Hybrid work policies may not only benefit employees but also help the employer to respond to employees' demands to reduce labor costs, access an expanded labor pool, reduce expenditures on office space and location, and comply with environmental mandates (Nilles, 1988; Olson, 1989; Bernardino, 1995).

The main research question of this study is how far telework influences transport demand. There is a long-standing interest in researching the intricate relationships between work arrangements, telework and activity travel demand (e.g., Salomon 1986; Nilles 1988; Mokhtarian 1991; Moeckel 2017; Lavieri *et al.* 2018; Shabanpour *et al.* 2018; Wang and Ozbilen 2020). It is clear that commutes constitute a large part of daily travel and bring the transport network to peak load during rush hours. Despite the potential to smooth peak volumes due to reduced commuting activity, the net effects are not that clear. Telecommuting could have adverse effects such as promoting urban sprawl (Bernardino, 1995) or inducing non-work travel, thereby substantially offsetting reduced commuting activity (Kiko *et al.*, 2024). In short, we need a behavioral approach to understand adjustment processes and evaluate policy implications. Further, the literature shows that home office adoption varies greatly between the countries and potentially even cities (Dingel and Neiman, 2020). A case study for Zurich is therefore justified and presented in this report.

To answer the research question, a clear understanding of home office access and frequency choices as well as hypothesized pathways along which telework impacts transport behavior is required. One such pathway is via mobility tool ownership (MTO), i.e., the attractiveness of owning a set of mobility tools depends on the telework frequency. Mobility tool ownership in turn is an important constituent of mode choice (Schmid *et al.*, 2023) and thus of the transport equilibrium.

Another pathway is alternative activity patterns of the home office population. In the spirit of Wang (2023) we have to acknowledge, that the home office population might be particularly (im-) mobile in the absence of the home office treatment. A simple group comparison potentially leads to biased conclusions. We therefore design different heuristics to impute activity patterns of the home office population and test in how far our assumptions drive the results.

We first investigate in a stated preference (SP) setting, whether or not hybrid work policies (work arrangement characteristics) have the potential to (dis-) incentivize telework. In a subsequent SP, the home office population was asked to reassess their mobility tool portfolio under different WFH scenarios. These two SPs result in a set of discrete choice models, capturing home office access, the preferred telework frequency (given access) and the preferred mobility tool ownership. These models are then used to generate a synthetic MATSim population for a buffered area around Zurich (accounting for inbound commutes). Heuristic strategies are designed to impute activity patterns for this population. The calibrated MATSim model is then leveraged to compare mobility behavior in the new normal, characterized by a large population share adopting home office, to the pre-pandemic benchmark.

The report is structured into four main sections. Section 2 summarizes the relevant literature, Section 3 elaborates on the survey methodology, Section 4 presents the econometric models used in the MATSim simulation and Section 5 contains the main MATSim analysis.

2 Literature

We organize the literature review as follows: Literature investigating telework adoption is divided into pre-pandemic and inter-post-pandemic. Subsequently, technical work on how to model telework is presented. Literature on survey work and stated-preference experiments in the context of working from home and mobility tool ownership respectively is discussed. Systemic approaches looking at telework and transport demand implications conclude the review.

2.1 Telework pre-pandemic

As noted by Asmussen *et al.* (2024) there was a healthy body of literature on the topic prior to the pandemic, though most of it only focused on telework adaption (e.g., Hotopp 2002; Vana *et al.* 2008; Ettema 2010; Lila and Anjaneyulu 2013; Kazekami 2020). Similarly, the home location was almost always assumed to be the only telework location (e.g., Groen *et al.* 2018; Kaplan *et al.* 2018; Silva-C *et al.* 2019), abstracting from the hybridization of the workplace (with telework centers or other third party facilities as alternatives) (Asmussen *et al.*, 2023).

Asmussen *et al.* (2023) further identified a limitation of these earlier studies to be the lack of incorporating the employees' preferences. Sheather and Slattery (2021) and Hopkins and Figaro (2021) argue that employers and managers need to start being more sensitive to the perspectives of their employees when designing hybrid work arrangements. Only a few studies were also investigating the frequency choice (e.g., Popuri and Bhat 2003; Singh *et al.* 2013; E Silva and Melo 2018).

With regards to drivers in the telework adoption, Drucker and Khattak (2000) report that car drivers have a higher propensity to telework. However, there could be a reverse causality, i.e. teleworkers choose to own a car. Meanwhile, Groen *et al.* (2018) and Cetrulo *et al.* (2020) find vast differences in telework opportunities across economic sectors. Earlier studies have generally found that part-time workers, those with long commutes, those residing in high-density urban areas, workers living closer to non-work and leisure activity opportunities, and those working in small-sized firms tend to telework more (e.g., Zhang *et al.* 2020; Caldarola and Sorrell 2022). Asmussen *et al.* (2024) summarize, that the overarching conclusions from the early literature are that teleworkers are typically young, holders of formal high education degrees, technologically savvy, and belong to urban households with higher income.

2.2 Telework inter-post-pandemic

During the early days of the pandemic sparking interest in telework as an option to contain the spread of the virus, Dingel and Neiman (2020) asked the question, how many jobs can be done remotely (taking a purely technical classification of telework access, completely abstracting from the preference and frequency dimension). This body of work (see also Gottlieb *et al.* 2021) suggests that significant variation across countries, cities and industries exist. For high-income countries a share of around 40% could fully shift to home office.

Similar to pre-pandemic research, telework adoption still is the main focus (e.g., Nguyen 2021; Danalet *et al.* 2021, 2022; Bick *et al.* 2023; Appel-Meulenbroek *et al.* 2022). However, there now is growing interest in understanding home office frequency choices (e.g., Zhang *et al.* 2020; Hensher *et al.* 2021; Heiden *et al.* 2021; Mohammadi *et al.* 2023; Yamashita *et al.* 2022; Ton *et al.* 2022; Asmussen *et al.* 2023). Various econometric methods are employed, ranging from multi-variate analysis such as ordinal, count or multiple discrete-continuous models (Asmussen *et al.*, 2024).

In general, the results from the more recent work tends to align with the pre-pandemic ones, with women (especially single women with children), young individuals, self-employed workers, employees in white-collar corporate jobs, high income earners and those with a long commute time having a higher propensity to work remotely. In contrast though, these after COIVD studies also suggest a narrowing of heterogeneity in telework adoption and frequency, with fewer sociodemographic and work-related variables governing the telework adoption/frequency (Asmussen *et al.*, 2023). Meanwhile, Zhang *et al.* (2020) point out occasional inconsistencies (for the effects of gender, presence of children and married employees), suggesting potential interaction effects.

Beck *et al.* (2020) predict a sizeable increase in the level of telework in the post-pandemic world. Contrasting the findings by Dingel and Neiman (2020) only few occupation classes were found to impact the home office decision significantly. However, the pandemic might have had a smoothing effect on industry differences with recommended or enforced home office duties in place. They further find evidence that larger cities have a higher home office share and that the probability to work remotely increases if an individual believes to be more productive when working from home, suggesting a potentially positive productivity-enhancing self-selection. The appropriateness of the workplace at home strongly governs home office decisions.

With regards to preferred remote workplace locations, Asmussen *et al.* (2023) and Stiles and Smart (2021) find that home only is the most prominent option casting doubt on telework centers being a viable alternative.

Various survey instruments have been devised to monitor the telework evolution during the pandemic covering many different countries (Barrero *et al.*, 2022; OECD, 2021; Beck and Hensher, 2020; Beck *et al.*, 2020; Hensher *et al.*, 2021). The authors agree that hybrid work forms are here to stay with two to three days being the most prominent frequencies.

2.3 Modeling telework

Mokhtarian and Salomon (1994) argued, that one should differentiate possibility, preference, and choice and that possibility is governed by several constraints (e.g. job unsuitability or manager disapproval). A theme that is widely acknowledged and incorporated in various econometric modeling approaches. In subsequent work, they further scrutinize whether these constraints should be part of the utility specification or choice set formation Mokhtarian and Salomon (1996). They conclude that the first is superior (at least in their model specification).

Similarly, Haddad *et al.* (2009) suggest differentiating four conceptual dimensions: opportunity, choice, preference and frequency. Work acknowledging these dimensions usually employs Heckman-style selection mechanisms (e.g., Popuri and Bhat 2003; Sener and Bhat 2011; Singh *et al.* 2013). Meanwhile, a plethora of work only considers two dimensions at a time (e.g., option as a prerequisite to observe a frequency choice).

Multi-variate modeling approaches accommodate common unobserved factors. Neglecting such common factors can lead to inconsistent estimation (as errors are no longer normally distributed but truncated-normal). A question then becomes, what multi-variate error distribution should the modeler assume. One prominent assumption is a multi-variate normal. Sener and Bhat (2011) allow for flexible error distributions by employing a copula-based sample selection model of telecommuting choice and frequency. They conclude that the analyst risks the danger of incorrect conclusions regarding dependency in the telecommuting choice and frequency behavioral processes, as well as inconsistent and inefficient parameter estimates, by imposing incorrect dependency structures or assuming independence between the two behavioral processes.

Yet another complexity arises if one accepts the endogeneity of several choice dimensions and does not want to apriori assume a causal direction. Paleti *et al.* (2013) develop an integrated model of residential location, work location, vehicle ownership, and commute tour characteristics. However, such fully integrated approaches are rare.

If the frequency dimension is considered at all, it is handled in various ways: Either as a count over different time horizons (e.g. weekly or monthly) or on an ordinal scale (e.g. "Always", "Several times per week", "Several times a month", etc.) as in Shabanpour *et al.* (2018) or Heiden *et al.* (2021). As a consequence, several modeling frameworks can be employed, most prominently multinomial logit and ordered logit or probit (Drucker and Khattak, 2000).

Further, the zero frequency is treated differently: Some treat it as part of the frequency range (e.g. Beck *et al.* 2020), while others consider telework adoption separately (as the previous discussion on selection mechanisms highlighted).

It still holds true, that the interplay between employers and employees is hardly ever approached (see Bernardino 1995, Yen and Mahmassani 1997 and Brewer and Hensher 2000 for notable exceptions). It is rather argued that job-related attributes (such as firm size, economic sector, etc.) proxy the employer's position (Asmussen *et al.*, 2023).

2.4 Surveys and stated-preference experiments

Earlier studies were almost forced to use stated-preference (SP) data because of the very few telecommuters in revealed-preference (RP) data. However, while many of the before-mentioned work is based on SP data (in the sense of recalling or reporting in a hypothetical scenario such as after the pandemic) only little work exists employing classical SP choice experiments. Early work in that regard was done by Bernardino (1995).

This is somewhat surprising as it has been demonstrated early on, that an employee's willingness to telecommute is not exclusively a function of individual characteristics and attitudes, but also depends on characteristics of the work arrangement. This provides the leeway for organizations to make telecommuting more or less attractive (Bernardino, 1995).

Bernardino *et al.* (1993) scrutinize the adoption and telecommuting frequency choice under various scenarios: A choice task is characterized by different combinations of telecommuting frequency, schedule flexibility, salary, available equipment and cost responsibilities for a home-based program. They conclude that incurring some or all of the costs is more acceptable than a salary decrease. Further, an asymmetry between salary increase and decrease exists, where a decrease is more of an impediment to adoption than a salary increase is a stimulus.

Both employers and employees were surveyed and asked to design their preferred telecommuting program. Therefore their approach does not only allow to estimate the probability of choice but also the probability of a certain arrangement being offered as a prerequisite (Bernardino, 1995).

Focusing on employee preferences, Sullivan *et al.* (1993) present respondents with different scenarios, combining various levels of salary and telecommuting costs borne by the employees. Telecommuting costs can include acquiring a new telephone line or a personal computer. Other options are that the costs be totally borne by the employee, partially or totally borne by the employer. Under each scenario, respondents can choose to telework from home every day, several days a week, possibly telecommute or not telecommute. In contrast to Bernardino *et al.* (1993) the work arrangement is exclusively characterized by different cost implications and does not scrutinize other factors such as schedule flexibility.

Brewer and Hensher (2000) develop a framework within which employers and employees interact and make discrete choices in respect of a common objective - the determination of participation in telework. Their experiment emphasizes the importance of negotiation and bargaining. The attributes involved in the experiment are very different from the before mentioned and involve the level of contact necessary with other people, the amount of control over work tasks, the resulting productivity, access to information and career prospects. They find that employees would like to work more frequently remotely but are reticent about how their employers would respond. While their work focuses on the interplay between agents, it could be argued that some of the proposed attributes are endogenous to a job role and can not exogenously vary as a consequence of telework in real life. Concretely, one of the attributes reads: If I telecommute the *level of contact* necessary with other people for my work would be *lower, unchanged* or *higher*. However, the level of contact necessary is pre-determined by the job role and determines the feasible choice set.

Appel-Meulenbroek *et al.* (2022) investigates the preference regarding workplace location in an SP experiment, choosing between three varying in-person workplace alternatives and one work-from-home alternative. The in-person work alternatives are characterized by work environment attributes and work activity type. They analyse in how far the attractiveness of the workplace can induce employees to telework. They find that crowdedness and noise were important factors, while openness of the office layout had no effect. However, employees did not like workspace surrounded by regular conversations nor a busy floor where almost all surrounding desks are occupied.

Experimental approaches in the context of mobility tool ownership (bundle choices) are rare, probably because of the high dimensionality of attribute level combinations which make it difficult to construct complete and realistic choice sets. A prominent approach to tackle this difficulty is the stated adaptation design (e.g., Schmid *et al.* 2019; Erath and Axhausen 2010.

Alternatively, the choice task is drastically reduced, e.g. by only considering the trade-off between car and an annual season ticket ownership (e.g., Weis *et al.* 2010; Scott and Axhausen 2006 or by only considering one particular mobility tool, (e.g., Fang 2008; Jong *et al.* 2004; Hess *et al.* 2012).

2.5 Telework and transport demand

As already noted, there is a long-standing interest in researching the intricate relationships between work arrangements, telework and activity travel demand (e.g., Salomon 1986; Nilles 1988; Mokhtarian 1991; Moeckel 2017; Lavieri *et al.* 2018; Shabanpour *et al.* 2018; Wang and Ozbilen 2020). However, early studies predicting the impact of telework on travel focused almost exclusively on the substitution effect of telecommuting (Popuri and Bhat, 2003). New trips will likely be generated because of travel to telework centers or third-party work places, travel that was previously linked to the commute, travel generated by increased leisure time and more time-flexibility, or travel performed by other household members due to the increasing availability of a vehicle (e.g., Mokhtarian 1990, 2000; Kitamura *et al.* 1990). Further, accessibility to various activities is altered due to the shift of the primary work location, therefore changing the selected activity set and potentially allowing for a shift to non-motorized modes such as walking and biking. On the other hand, the car might be more freely available at the household level, since it is not occupied by the commuter (Bernardino, 1995).

Beck and Hensher (2021) suggest that a larger incidence of telework translates into better transport network performance, especially in larger cities due to reduced traffic congestion (see also Pendyala *et al.* 1991; Kitamura *et al.* 1990; Hamer *et al.* 1991) and crowding on public transport (PT). Further, peak traffic volumes can be reduced. This has considerable implications for transport planners since the capacity of critical infrastructure needs to match peak loads. With regards to mobility tool ownership, the authors argue that car becomes more attractive compared to public transport.

Beck *et al.* (2020) analyze the influence of WFH on modal-dependent commuting activity. The number of car commuting trips increases drastically as the population share working 0 days from home increases. Demand for public transport trips decreased which could be a direct consequence of hygiene concerns during the COVID-pandemic. Similarly, it is yet to be analyzed in how far these shorter-term mode choice decisions translate into changes in the longer run, i.e. mobility tool ownership choices. Except for Paleti *et al.* (2013), no studies have been found that research the impact of telework on mobility tool ownership.

For the case of Switzerland, Bundesamt für Statistik and Bundesamt für Raumentwicklung (2017), Ravalet and Rérat (2019), and Wöhner (2022) have examined the extent to which teleworking influenced mobility before the pandemic: commuter frequencies decrease, while trips for other activities increase. At the same time, the distances between home and workplace are on average around 50% longer than for individuals who do not regularly work from home. This rebound effect completely offsets the saved trips. Only individuals who exclusively work from home show lower travel performance. Ravalet and Rérat (2019) conclude that the possibility of working partially from home can lead to less frequent changes of residence and an increased tolerance for commuting over long distances.

Shabanpour *et al.* (2018) develop an integrated framework to provide empirical evidence of the potential impacts of home-based telecommuting on travel behavior, network congestion, and air quality. The analysis focuses on the Chicago region and its baseline scenario is a 12% population share with flexible working time schedules. They find that compared to the baseline, in the case when 50% of workers have flexible working time, telecommuting can reduce total daily vehicle miles traveled and vehicle hours traveled up to 0.69% and

2.09% respectively. Greenhouse gas and particulate matter emissions can be reduced by up to 0.71% and 1.14%.

3 Survey methods and response behavior

3.1 Introduction and motivation

The pandemic has fueled the adoption of hybrid work arrangements. Before the pandemic, working from home (WFH) was the exception rather than the rule and the formal setting was therefore likely to be agreed bilaterally. However, when a large share of the employees shifts to remote, the applicable work policies need to be revised. Are employees allowed to work from anywhere or only from a designated home office workstation? Who covers the increased electricity bill when the home suddenly becomes the office? Do employers contribute to necessary expenses to set up a productive home office environment? Further, business leaders taking a negative stance on home office threatened to implement salary decreases to incentivize people back to downtown. In how far do these policy dimensions matter for individuals' home office adoption and what are the resulting telework frequencies? Do they provide considerable stimuli to entice workers to the (home) office?

Habit formation takes time. Currently, observed home office frequencies do not necessarily reflect an equilibrium. Also, the only recently faded awareness of the virus might have played into the decision to avoid crowded office spaces or public transport and thus stay at home. An understanding of home office preferences beyond these real-world constraints is therefore important and suggests investigation with the help of stated preference (SP) surveys. This allows us to complement the current literature on the constituents of home office preferences beyond socio-demographic and job-task-related attributes as well as predicate such choices in the longer term. Such an understanding is essential for the field of transport since depressed commuting and potential alternative trips being generated in residential neighborhoods impact transport dynamics.

Our proposed survey framework and the data collected investigate a further hypothesized adjustment channel - mobility tool ownership (MTO). People might revise their MTO and readjust their mobility bundle as home office can be seen as a lifestyle change. In particular, the demand for public transport (PT) subscriptions was considerably depressed during the pandemic. As already alluded to, the spread of the virus and the adoption of home office were intertwined, making it difficult to disentangle the two effects on demand. Further, mobility tools (most notably the car) imply strong lock-in effects, as the tool only depreciates slowly. PT subscriptions on the other hand can be canceled quickly (usually within a year). As a natural consequence, MTO is rebalanced only infrequently, further complicating an understanding of the impact of telework. We therefore propose a second SP experiment, investigating the relation between WFH and MTO (car, car sharing, bike, E-bike and different PT subscriptions). As the reader will realize, the dimensionality of the set of realistic mobility tool bundle alternatives is enormous, leading to a dilemma of how to manage complexity and abstraction from real-world choices.

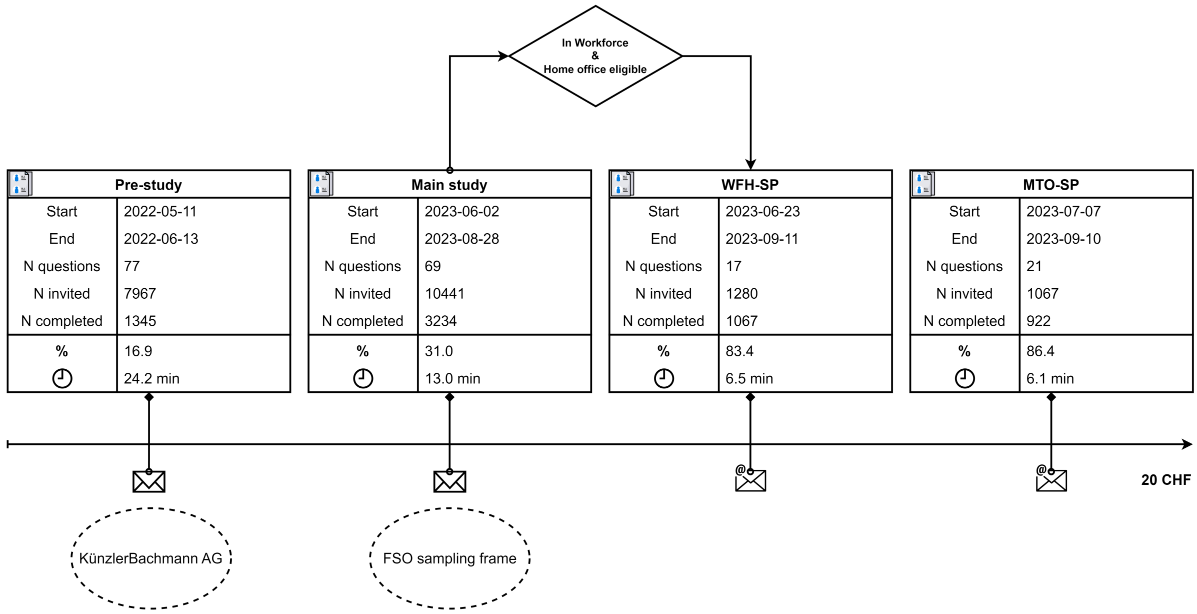
The data collected in this work therefore allows researchers to investigate the following research questions: What are the preferences for hybrid work arrangement characteristics? In how far do they impact adoption and the frequency choice? Are they of relevance, compared to other factors (such as socio-demographic and job-task-related attributes)? How do teleworkers rebalance their mobility tool portfolio, in light of such hybrid work arrangements? In short, a detailed understanding of WFH and its relation to MTO can be developed with the dataset. Item batteries allowing modelers to control for the home office feasibility (a dimension usually not considered) are also available.

The study focuses on the German-speaking part of Switzerland and over-samples residents of the city and canton of Zurich. Switzerland is a suitable study area since its economy features a high share of white-collar workers and its people usually own a diverse set of mobility tools. Zurich is a hub for the financial sector which had potentially undergone dramatic change over the course of the pandemic. For reasons of data security, privacy, etc. home office was not really possible before the pandemic. However, it is now.

10441 people from the Federal Statistical Office's sampling frame have been contacted by letter, of which 3234 individuals completed the first survey, resulting in a high-quality representation of the true population and a large array of SP choices.

The remainder of the chapter is structured as follows: In Section 3.2 we detail the four survey instruments of the pre and main study as well as discuss the SP designs. Section 3.3 reports the response behavior and Section 3.4 elaborates on home office treatment effects on MTO and resulting ownership shares. Section 3.5 highlights key characteristics of the data, such as current and expected home office shares and distributions over the weekdays. Section 3.6 conducts a factor analysis on the proposed measurement questions for the latent home office feasibility (teleworkability). Section 3.7 concludes.

Figure 1: Timeline of the surveys and key statistics.



3.2 Survey methods

The following sections elaborate on the structure of the survey instruments and detail the SP designs. Two different population samples from the German-speaking part of Switzerland have been recruited for the two main survey waves (the pre-study and the main study): For the pre-study, 7967 addresses have been bought from an address dealer, targeting age and gender marginals from the mobility and transport microcensus (MZ2021, Federal Office for Spatial Development and Federal Statistical Office 2021). For the main study, a stratified sample of 10441 individuals was received from the Federal Statistical Office. Respondents living in the canton of Zurich were over-sampled as the city and canton of Zurich partnered in this project. Further, the data was collected to estimate statistical models for MATSim, where scenario analysis was envisioned for that particular area.

Both samples were invited by postal letter to take part in the introductory survey. One reminder was sent, and for the main study, an incentive of 20 CHF was promised, upon completion of all three parts of the study. To anonymize participants and to link the responses, random five-letter codes were generated. As subsequent communication happened via E-mail, personalized links were distributed, leaving a trace of the individual identifiers.[1] Great emphasis was given to stress the importance of participating even when the current work situation is not suited for telework. This allows us to quantify the share of residents with home office access and estimate Heckman-type selection models in future work.

3.2.1 Pre-study

As only little academic work has investigated the importance of work arrangement attributes on the home office frequency choice, the main purpose of the pre-study was to identify attributes of relevance in the decision-making process required to design meaningful trade-offs in the SP. At the same time, this provided an opportunity to test the survey structure for *Stage I* (Section 3.2.3), shed light on possible adjustment channels (e.g., the connection between home office and residential relocation, or between home office and alternative activity patterns) and infer the home office population share.

Participants were asked to rank order a menu of proposed generic work arrangement attributes (Table 1) and subsequently distribute 100 points among their top four choices. The results are visualized in Fig. 2 and suggest that employees place high value on efforts to maintain collegiality, corporate identity, and flexibility. Flexibility in choosing when to work from home, where to work from, and time management when working from home. Meanwhile, financial incentives are of less relevance. The reader can later confirm in Section 3.2.4 that we accounted for this revealed attribute importance in the SP design.

3.2.2 Main study

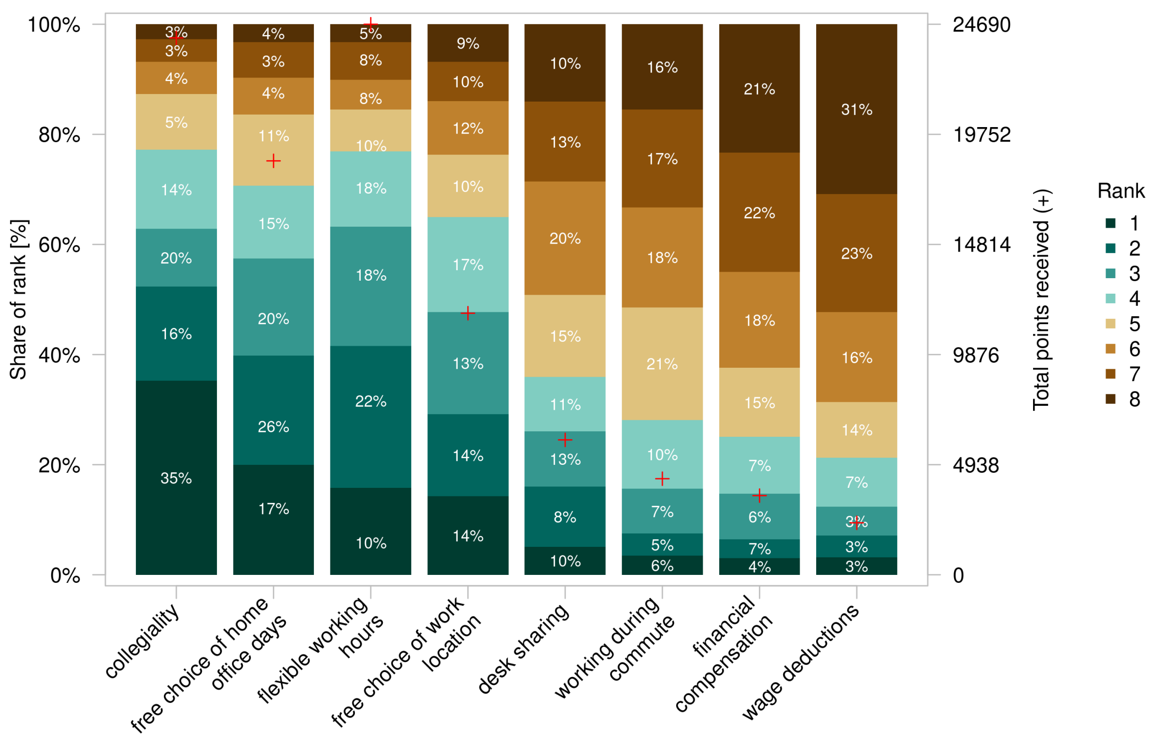
The main study consists of three stages: A classical online questionnaire and two SP experiments. The survey instruments are introduced in the next sections in turn.

[1]Researchers should avoid including the l (lowercase L) and I (uppercase i) in such identifiers.

Table 1: Generic attributes tested in the pre-study

Attribute	Explanation
Collegiality	The employer takes specific measures to promote the flow of information as well as the feeling of togetherness.
Flexible working hours	Possibility to freely arrange working hours. You are also allowed to stay away from work for longer periods during the home office, provided you complete your tasks and compensate for the working time.
Free choice of home office days	Possibility to freely choose available home office days. You are free to decide on which days of the week you work from home.
Free choice of work location	You are free to choose the location at which you operate your home office, as long as you are in Switzerland.
Desk sharing	At your company's office, you do not have your own office space but have to work in desk-sharing.
Working during commute	If you decide to work in the office, you may work on the commute and count this time to your working hours.
Financial compensation	All additional costs caused by home office (office supplies, heating costs, internet, etc.) are borne by the employer.
Wage deductions	If you work in home office, your salary will be marginally adjusted (assume here a salary adjustment of 2% per home office day). The wage deductions can also be realized indirectly via reduced fringe benefits.

Figure 2: Attribute importance.



3.2.3 Stage I: Introductory survey

At the first stage, respondents were invited to take part in an online survey, asking for their socio-economic information, household structure, current home office status, work, and residential situation as well as mobility behavior and mobility tool ownership. The instrument's structure is detailed in Table 2, starting with two screening blocks. Only individuals currently in the workforce qualified for participation. Further, WFH-related questions were only asked to individuals having a job suitable for (partial) remote work.

An item battery of Likert-scale questions was proposed to investigate a person's theoretical home office feasibility. These questions include job characteristics, the residential environment, and personality traits. A factor analysis was conducted on these items and the results are outlined in Section 3.6.

Table 2: Structure of introductory survey

Topic	Question	Remark
Intro	User consent	Welcome participant; Reminder to participate even if teleworking is not possible/allowed
Screening employment	Work status	Only proceed if respondent is in workforce
Screening WFH	Feasibility to perform work partially remotely; Employer's stance on home office; Is the option to telework provided; Current home office frequency and free-choice	Understand the current WFH status; Identify display logic for WFH-related questions
Sociodemographics	Marital status; Education	Further sociodemographics can be inferred from address register
Household	Household size; Household and personal income	
Residence	Type of residence; Size of residence; Monthly additional costs (e.g., heating and hot water); Access to second residence	Residential characteristics determine the quality of the home office environment; Home office as an option to spend more time at second residence

Work	Full-time or (multi-) part-time employed; Workload (as % of full-time equivalent); NOGA sector; Work location (geo-referenced); Firm size; Occupation's ISCO classification; Type of work contract (e.g. permanent vs. fixed-term); Shiftwork; Work schedule (e.g. fixed number of working hours per week); Managing people	The job role is expected to highly influence the home office access and frequency
Mobility	Driving license; Mobility tool ownership pre-COVID; Current mobility tool and PT season ticket ownership; Specifics of current car; Parking available (at home and work location); Main commute mode	Investigate COVID-induced change in MTO; Inertia/habits in MTO
WFH I	Work status before and during COVID; Home office frequency before COVID and during lockdown	Frequency during lockdown can be used as a proxy for maximum home office feasibility
WFH II	Budget required to set up home office workstation; Does employer contribute to these expenses; Desk sharing in office	Reference values for SP and pooled RP-SP estimation
WFH III	Preferred home office weekdays; Maximum number of home office days set by employer; Degree of coordination (office attendance); Reference values for SP (see SP attributes); Characteristics of home office workstation	Reference values for SP and pooled RP-SP estimation

Teleworkability	Job's degree of digitization; Job requires physical interaction; Work context (specialized work environment); Tech savyness; Personal suitability; Residential suitability; Home office workstation suitability	Indicators for measurement equations (for latent teleworkability variable)
Psychometrics	Minimal item battery to identify character traits	Possibility to include character traits as latent variables; Home office as an option to avoid personal interaction, to shirk, etc.
Outro	E-mail address	Further communication is done via E-mail

3.2.4 Stage II: Work from home SP

Individuals who were identified as home office eligible were invited for the second stage - the work from home SP. The inclusion criterion encompassed being in the workforce as well as having a work profile that allows for at least one home office day a week, irrespective of whether or not the current employer provides the option to work from home.

The selection of attributes is largely inspired by Bernardino (1995) and the learnings from the pre-study as elaborated in Section 3.2.1. Despite the participants neglecting the relevance of salary adjustments in the pre-study survey, they were included in the design. First, (dis-) incentivizing home office via this channel has been debated and proposed by some prominent industry leaders, and second, the attribute acts as a natural cost component, allowing the modeler to interpret other attributes in a monetary (willingness to pay) space.

Attributes and their levels are presented in Table 3. Notably, three attributes (*hardware budget, additional cost* and *salary adjustments*) imply a cost component and a marginal utility of one Swiss franc received (or not) for the envisioned purpose. It is to be tested whether or not the monetary utility equivalent is constant across these three purposes. *Coordination* could potentially have both a positive and negative utility implication: On the one hand, it reduces personal flexibility while on the other, it coordinates office attendance. *Desk sharing* captures the idea of office restructuring, using office space more

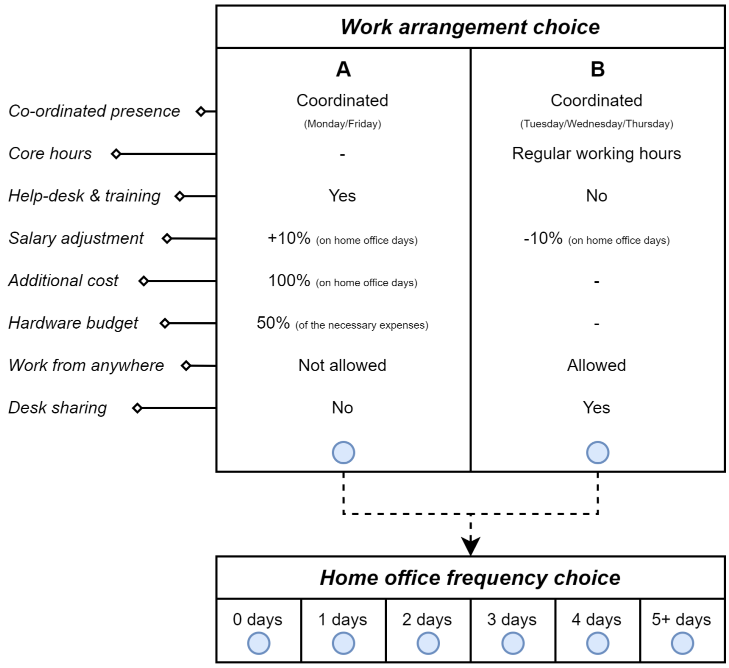
Table 3: Attributes and levels of the WFH-SP experiment

Attribute	Level	Remark
Coordinated presence	Monday/Friday Tuesday/Wednesday/Thursday	Office attendance of team members is coordinated on these days.
Core hours	None Regular working hours	Employee can freely allocate working time or is expected to work during regular working hours.
Help-desk and training	Yes No	Help desk for technical assistance and training for effective home office collaboration and management.
Salary adjustment	-10% No salary adjustment +10%	On an hourly wage basis for home office hours.
Additional cost	No contribution 50% 100%	Compensation for increased energy consumption among others.
Hardware budget	No contribution 50% of the necessary expenses 100% of the necessary expenses	Yearly budget for setting up a productive home office work station.
Work from anywhere	Allowed Not allowed	Only within Switzerland.
Desk sharing	Yes No	Restructuring of the office space.

efficiently in the absence of home office employees. *Help and training* implies support for technical difficulties as well as training - not only fostering effective collaboration via digital channels but also a successful home office culture. The full factorial was reduced according to the principles of D-efficiency. Each participant was asked to complete four choice tasks.

Bernardino (1995) include the telecommuting frequency as an attribute of the work arrangement itself, potentially resulting in unrealistic levels. In contrast, we suggest a sequential choice setting where respondents are first asked to choose their desired work arrangement and subsequently reveal their preferred frequency (given the characteristics of the previously selected arrangement). An example of one such combined choice task is given in Fig. 3.

Figure 3: Example of a choice task for the work from home stated-preference experiment.



3.2.5 Stage III: Mobility tool ownership SP

Conducting a realistic SP experiment in the context of mobility tool ownership is a complex task: The characteristics of each proposed mobility tool must be precisely specified, not leaving room for assumptions. Further, some individuals or households share multiple mobility tools of the same type. Lastly, strong interdependencies between several tools might exist (e.g. negative correlation between car ownership and GA). Therefore, the decision process involves intricate trade-offs, potentially considering all the household members' preferences collectively, bargaining, and choosing a bundle rather than trading-off attributes separately for each mobility tool. So clearly, the SP should feature a bundled choice such that the specifics of one mobility tool can be evaluated against the specifics of all the other available tools.

The first dimension of a bundle should involve the availability of each mobility tool considered. The second dimension elaborates on the characteristics of each tool. In our study, we consider car, PT subscription (national season ticket (GA) or regional subscription), half-fare card (HT, where you pay half the price for an individual journey using PT), car sharing subscription, and bicycle as separate tools, i.e., five tools in total. We follow Becker *et al.* (2017) but add (E-)Bikes and HT as additional tools. An individual can now bundle these five tools together, resulting in $2^5 = 32$ possible combinations/bundles and, thus, alternatives. Notably, these alternatives differ only in the availability of each tool (*between mobility tool trade-off*) and do not enforce trade-offs at the mobility tool level (e.g., deciding between two different cars - *within mobility tool trade-off*).

Clearly, it is a curse of dimensionality, and the researcher must abstract the choice task in some way. An unlabelled approach was investigated in a pre-test, asking the respondents to choose among two alternative bundles. However, participants perceived the experiment as too complex and abstract from reality (likely, both of the proposed bundles are far from actual preferences, potentially not even featuring the favorite type of mobility tool).

Therefore, a conceptually simpler design was proposed, presenting one concrete option for each mobility tool and asking the respondents to compose a bundle from the menu. Fig. 4 depicts one choice task. Each respondent was presented with four such choice tasks in total. The participants were introduced to the choice task with the following text:

In this survey, we want to determine how far **home office** impacts your **mobility tool ownership** choices.

On the following pages, you are asked to choose between different mobility tools under various home office scenarios. Imagine that all your current mobility tools have expired and need to be **renewed** anyways. This is what a choice task looks like:

(see Fig. 4 with selected PT subscription and bicycle).

In the example above and given the home office situation presented, I would choose to own the PT subscription and the bicycle.

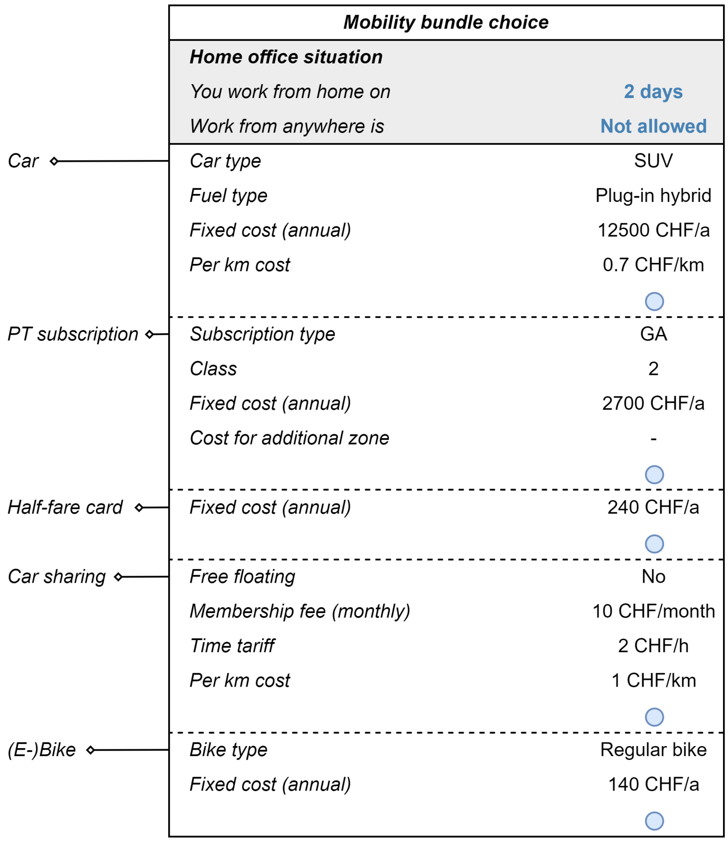
- In the black box, a hypothetical home office situation is presented. The scenario consists of **how many days a week you work from home** and whether or not **working from anywhere (within Switzerland)** is allowed. The home office frequency is based on your answers from previous surveys: Either it matches your stated preference or it is based on your answer regarding how many days you could shift to home office given your work tasks.
- Please take a moment to reflect on what your life and mobility behaviour would look like, **given the home office situation** presented.
- Each choice card contains a **car** offer, a **public transport (PT) subscription** offer (either GA or regional season ticket), the price of the **half-fare card**, a **car sharing** service as well as a **bicycle** (either regular or E-Bike) offer. The exact attributes and what they imply are subsequently introduced.
- Last, you can choose for each of the five mobility tools whether or not you would like to own these tools at the conditions outlined. There are no other options available. F.ex. if you do not want to own the presented car, you don't have any other car available. So think about what composition of mobility tools would best match your needs given the home office scenario.
- Apart from the costs presented, you can assume that **all other prices are as of today** (e.g., fuel prices, single-fare train tickets, electricity prices, etc.).

While conceptually simpler, this design emphasizes the availability trade-off and abstracts from trade-offs between mobility tools of the same type (not choosing the depicted car implies not owning a car at all[2]). Hence, a particular mobility tool is chosen if the net benefit/utility is positive. That is, even if a participant has a strong aversion against a particular car attribute level (say car type is *Luxury or sports car*), he might still choose it if the disutility of not owning a car outweighs the preference aversion against that attribute level.[3] It is worth mentioning, that the stated choices collectively still allow the modeler to investigate preferences for a particular type of mobility tool: Let's assume we observe several choices where the same (similar) bundle is presented except for the

[2]Providing an outside option (e.g., "another car") is not sensible in this context.

[3]The question becomes whether the (dis-) utility of not owning a car is constant across choice occasions. We might expect that it depends on the characteristics of the other mobility tools. For example, if a very cheap GA is proposed, then not owning a car might be acceptable. Beware of potential modeling implications.

Figure 4: Example of an individualized choice task for the mobility tool ownership stated-preference experiment.



car alternative. Therefore, the (dis-) utility of not owning the car is constant in these choice occasions. The decision to let the car be part of the bundle must therefore be purely attributed to the characteristics of the car (and potential interaction effects with the other tools).

An individual-specific maximum home office frequency was inferred to ensure a realistic WFH variation: The largest value of either the current WFH frequency, the maximum feasible frequency (as asked in the introductory survey), the free-choice frequency, or the observed choices in the SP was selected as the upper bound. Subsequently, a random draw from an interval ranging from zero to this individual-specific maximum was taken. The free-choice encompasses a scenario where employees do not face any constraints imposed by the employer (such as a maximum number of days where WFH is allowed) but still realistically accounts for the job's suitability.

Further, mobility tools and their characteristics were constructed carefully. In particular, realistic cost implications of owning (and using) a car required special consideration, not least to provide comparable numbers for the trade-off between the car and the other mobility tools. For example, the fixed cost of buying a car has to be compared to the annual expenses of a PT subscription. The car depreciates while the PT subscription does not. Moreover, the actual cost of owning a car includes taxes, insurance coverage, and other expenses (of which users are not necessarily aware). To be accurate about all the underlying assumptions, the website of the Swiss Touring Club (TCS)[4] was scraped: For each vehicle class and fuel type combination, the specifics of all available cars were collected and then averaged. This yielded an *archetype* for the particular car and fuel type combination and served as the basis for a pivot approach. As fixed costs depend on the cantons and per km cost on annual mileage, the canton of Zurich and 15000 km were selected as references. The mileage roughly corresponds to the average annual distance driven as reported in MZ2021. The work resulted in a python package *tcsscraper*[5] providing an API to retrieve many variables for the current Swiss car fleet.

As evident in Fig. 5 there is an almost perfect linear relation between fixed and variable cost. Similarly, the annualized costs of owning a car are higher than the price of a GA subscription. While an SP should decorrelate the different factors (which is guaranteed by our pivot approach), we reasoned that a somewhat realistic reference benefits the otherwise abstract choice task.

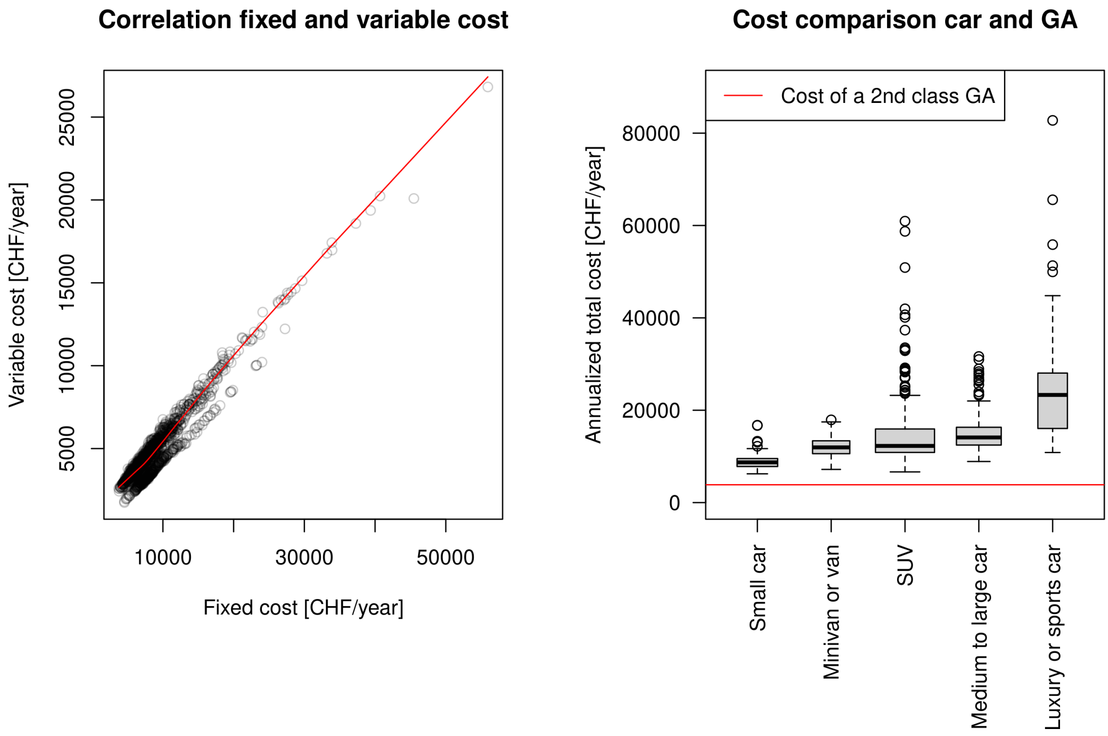
The generation of the random design included the following steps:

1. Generate the full factorial (resulting in over 11 million possible attribute level combinations).
2. Apply constraints (i.e., only show the PT zones included if the PT type was *regional subscription*).
3. Replace effect codes: Substitute reference values and apply the cost structure as imposed by the design. For example, if the attribute *car fixed cost* was high, then the substituted archetype's fixed cost was increased by 30%. Similarly, the cost of the PT subscription depends on the class.

The attributes as well as assumed reference values are presented in table Table 4. The marginal cost of an additional PT zone for the fare network was based on the case of

[4]`https://www.verbrauchskatalog.ch/index.php`
[5]`https://github.com/dheimgartner/tcsscraper`

Figure 5: Characteristics of the cars' dataset.



Zurich[6] and its validity for other networks was examined.

[6]`https://www.zvv.ch/zvv-assets/abos-und-tickets/pdf/broschuere_tickets_preise.pdf`

Table 4: Attributes and levels of the MTO-SP experiment

Alternative	Attribute	Level	Reference	Remark
Car	Type	Small car		
		Medium to large car		
		Minivan or van		
		SUV		
		Luxury or sports car		
	Fuel	Gasoline		
		Diesel		
		Electric		
		Hybrid		
		Plug-in hybrid		
	Fixed cost	0.7 (-30%)	Inferred from archetype	Fixed costs include amortization, garaging costs, insurance,
		1		and taxes. The price of the car is reflected in the fixed cost
		1.3 (+30%)		(amortization).
	Variable cost	0.7 (-30%)	Inferred from archetype	Per kilometer cost, including depreciation of the car's value,
		1		fuel or energy costs, tire costs and maintenance.
		1.3 (+30%)		
PT	Type	GA		
		Regional season ticket		
		Half-fare		
	Class	First		Cost multiplier of 1.7 for first class
		Second		
	Fixed cost	0.7 (-30%)	3860 CHF/year (GA)	
		1	782 CHF/year (Regional)	
		1.3 (+30%)	185 CHF/year (Half-fare)	

	Additional zone	0.7 (-30%) 1 1.3 (+30%)	40 CHF for additional zone	Only for regional season ticket
Bicycle	Type	Regular bike E-bike (up to 25 km/h) E-bike (up to 45 km/h)		
	Fixed cost	0.7 (-30%) 1 1.3 (+30%)	200 CHF/year (regular) 600 CHF/year (25 km/h) 100 CHF/year (45 km/h)	Fixed costs include amortization, maintenance, and insurance. The price of the bicycle is reflected in the fixed cost (amortization).
Car sharing	Free-floating	Yes No		Whether or not the car sharing is station-based or free-floating.
	Membership fee	10 CHF/month 15 CHF/month 20 CHF/month		
	Time tariff	2 CHF/h 3 CHF/h 4 CHF/h		
	Km tariff	0.8 CHF/km 1 CHF/km 1.2 CHF/km		
Scenario variables	Work from home	0-5+ days	Individual-specific	Either the current WFH frequency, the maximum feasible frequency (as asked in the introductory survey), the free-choice, or the observed choices in the SP.
	Work from anywhere	Allowed Not allowed		

Each attribute was carefully introduced and individuals needed to confirm whether or not they understood its meaning. Similarly, people not familiar with the Swiss fare geography were asked to study an interactive map and familiarize themselves with the relevant zones.

3.3 Response behavior

As reported in Fig. 1, a strong relation between time complexity and response rates exists. Regressing median time on the response rate suggests that every additional minute decreases response rates by $3.9(\pm 2.3)$ percentage points. From this perspective, the twice-as-high response rate (compared to the pre-study) for the introductory survey can be explained. Participation in the SP experiments was similar and very high, despite their complexity.

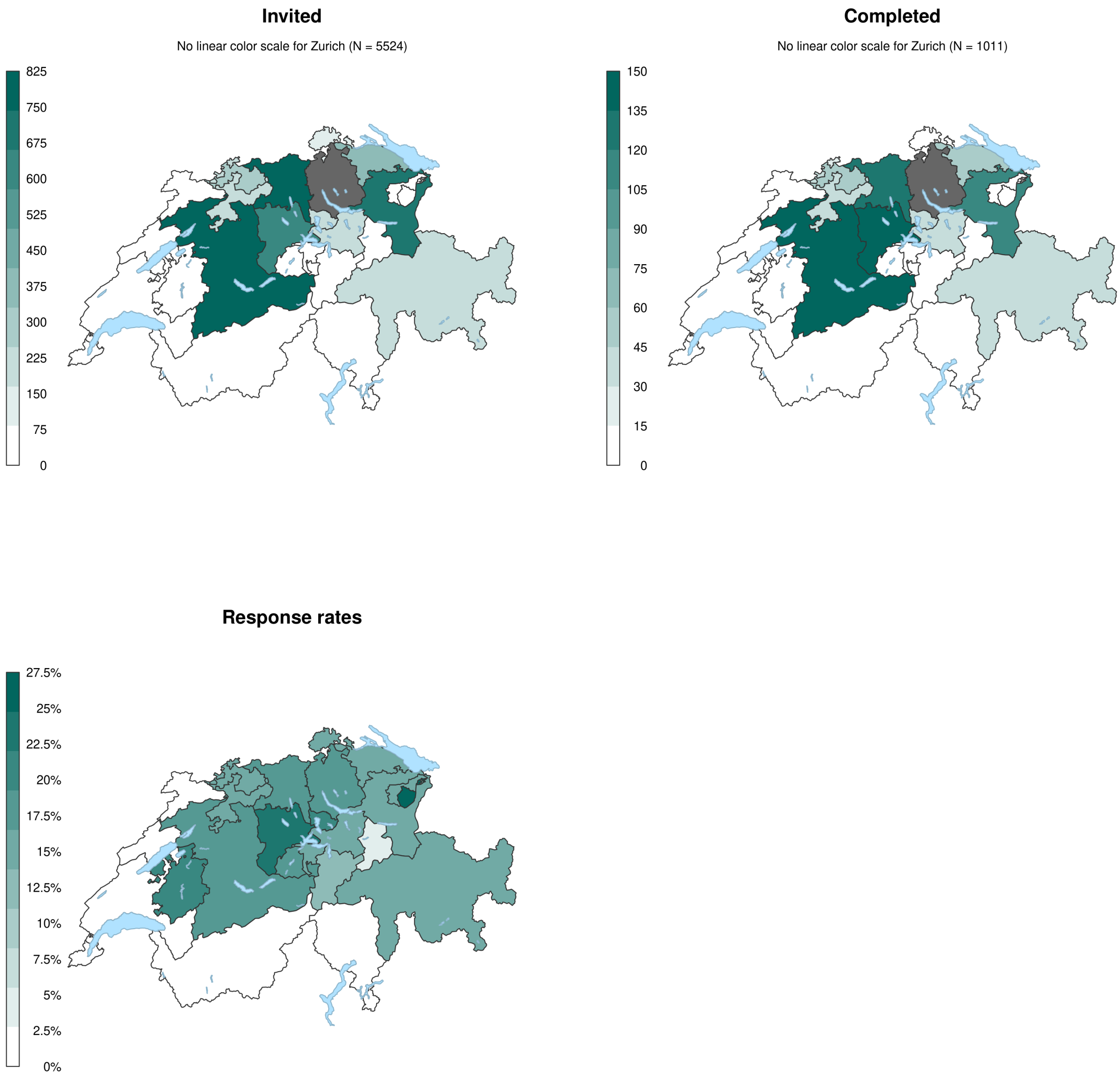
Cumulative survey response over time (Fig. 7) clearly shows the recruitment efforts: Both the pre-study and introductory surveys of the main study depict a kink when the reminder letter was received. The latter surveys show several of these kinks as the recruitment happened on a rolling basis via E-mail.

Generally, the shares as implied by the SP choices, do not reflect actual market shares but depend on the average condition. Nevertheless, the WFH frequency variation (Fig. 8) provides strong evidence that $2-3$ home office days is the preferred option. The deviation from the free-choice frequency (free-choice - chosen frequency) reveals that 44% of the stated frequency corresponds to the free, unconstrained choice. Meanwhile, 41% adjust the home office days only by a marginal day. The distribution of the differences is almost symmetrical, which can be read as follows: The average work arrangement conditions are balanced (some attributes favor more home office while others inhibit telework).[7] In the absence of any (dis-) incentives, respondents choose the free-choice frequency, while any deviation from it must be attributed to the applicable work arrangement conditions.

Fig. 9 highlights that SP implied ownership shares do not reflect actual shares, as expected. Car is under-represented, while PT subscriptions are over-represented. As already alluded,

[7] The slight left shift in the distribution can be explained with our experimental setting: Respondents first choose the desired work arrangement potentially slightly impacting the overall balance.

Figure 6: Cantonal distribution of survey participants.



the single proposed car attributes might be so unfavorable that respondents substitute car for PT or car sharing (while in the real world, they would simply look for another car instead). Meanwhile, the half-fare card is comparably less attractive, potentially because it is a complement to the PT subscriptions (which gained hypothetical ownership share as just explained).

Figure 7: Survey response over time.

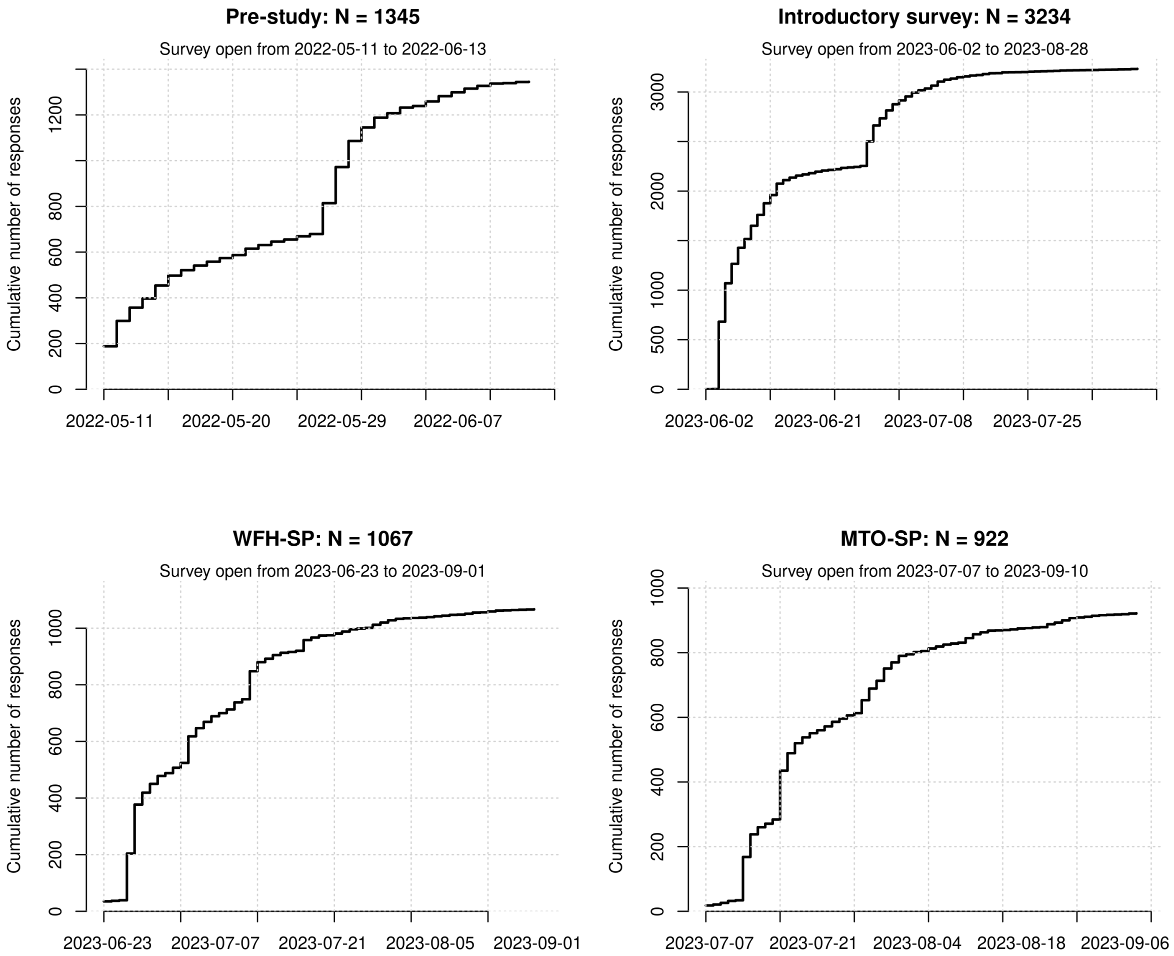


Figure 8: WFH choice variation.

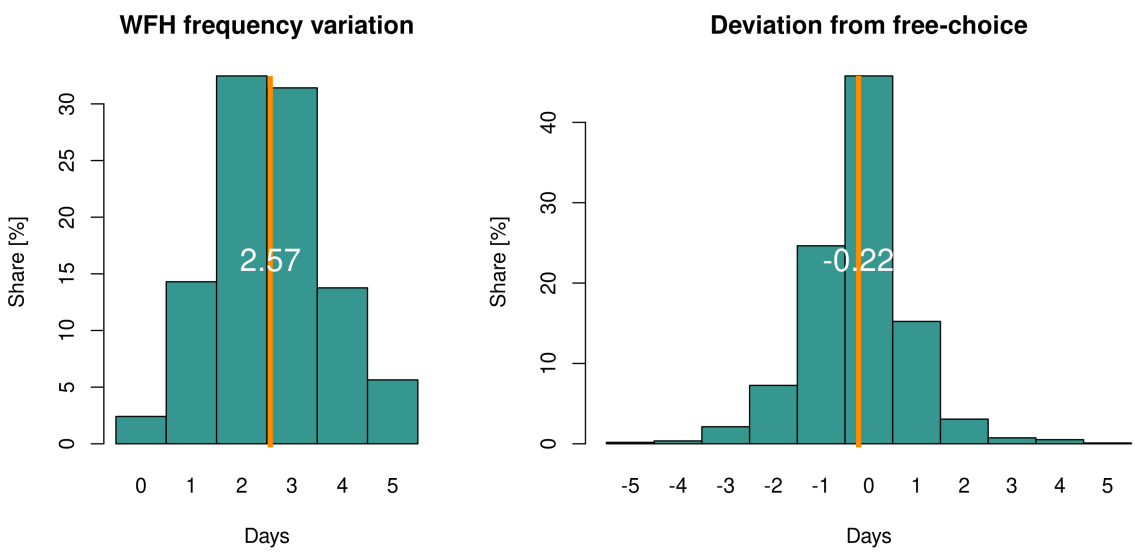
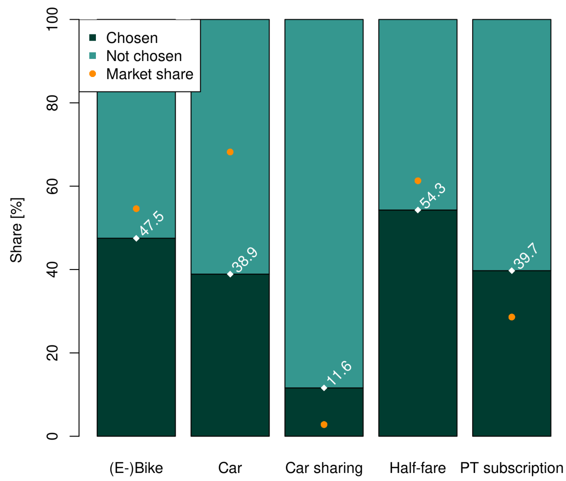


Figure 9: MTO choice variation: Comparison of RP market shares (orange dots) and SP choice shares (white dots).



3.4 Home office treatment effects

Shifting attention to the two scenario variables (home office frequency and work from anywhere), general trends can be observed: Fig. 10 visualizes home office treatment effects, where choice shares are plotted against the home office frequency.

Since the home office frequency has been randomly assigned in the choice experiment, we can expect the effects to reflect unbiased average treatment effects (ATE). The estimates of simple probit models, regressing the WFH frequency on the observed choice, are reported in Table 5. Three out of the five mobility tools show significant estimates: For car and PT a negative effect can be observed, whereas HT can expand its ownership share as a consequence of increased telework. To comment on the magnitude, the ATEs can be consulted. If an individual works from home one day more, he is 1.4 percentage points (pp) less likely to own a car (which can also be read as a reduction in overall ownership share). PT subscriptions show a stronger negative effect with a 3.1pp decrease in ownership share and HT has a positive ATE of 2pp (suggesting a substitution effect from PT subscriptions to HT).

Let's assume that we transit from the status quo (1.65 days/week) to a world where every individual is allowed to work their desired number of days from home (2.32 days/week). In a bootstrap exercise, we simulated the model-implied ownership share distribution

Figure 10: Correlation between home office frequency and MTO choice.

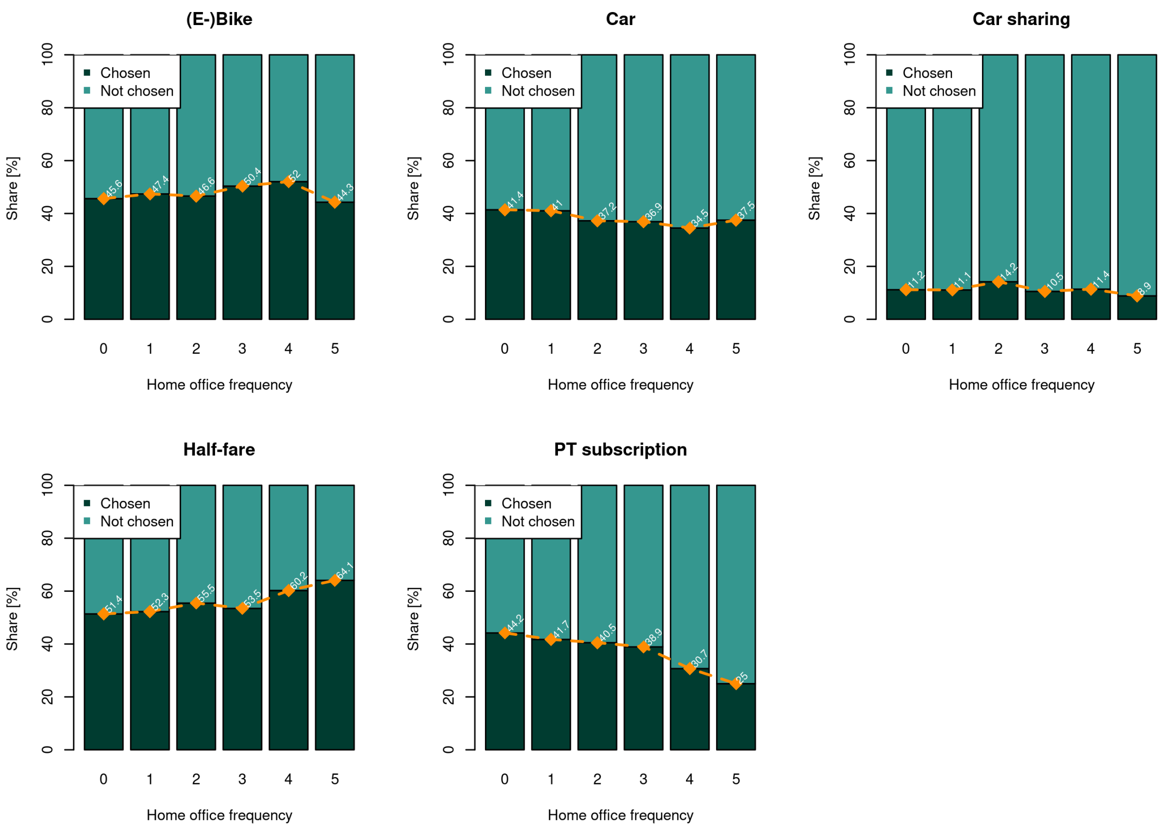


Table 5: Home office treatment effects: Probit modeling results regressing WFH frequency on MTO choice

Mode	Estimate	Std. Error	p-Value	Sig.	ATE
Car	-0.037	0.014	0.009	**	-0.014
PT	-0.083	0.014	0.000	***	-0.031
HT	0.052	0.014	0.000	***	0.020
Car sharing	-0.007	0.018	0.693		-0.001
(E-)Bike	0.020	0.014	0.156		0.008

Note: *5%, **1%, ***0.1%

(Fig. 11) and computed 95% confidence intervals.[8]

Concerning the second scenario variable (work from anywhere), no treatment effects can be observed (Fig. 12).

[8]Recall that the confidence levels reported in Table 5 are based on two-sided hypothesis test.

Figure 11: Bootstrapped distributions of the model-implied ownership shares.

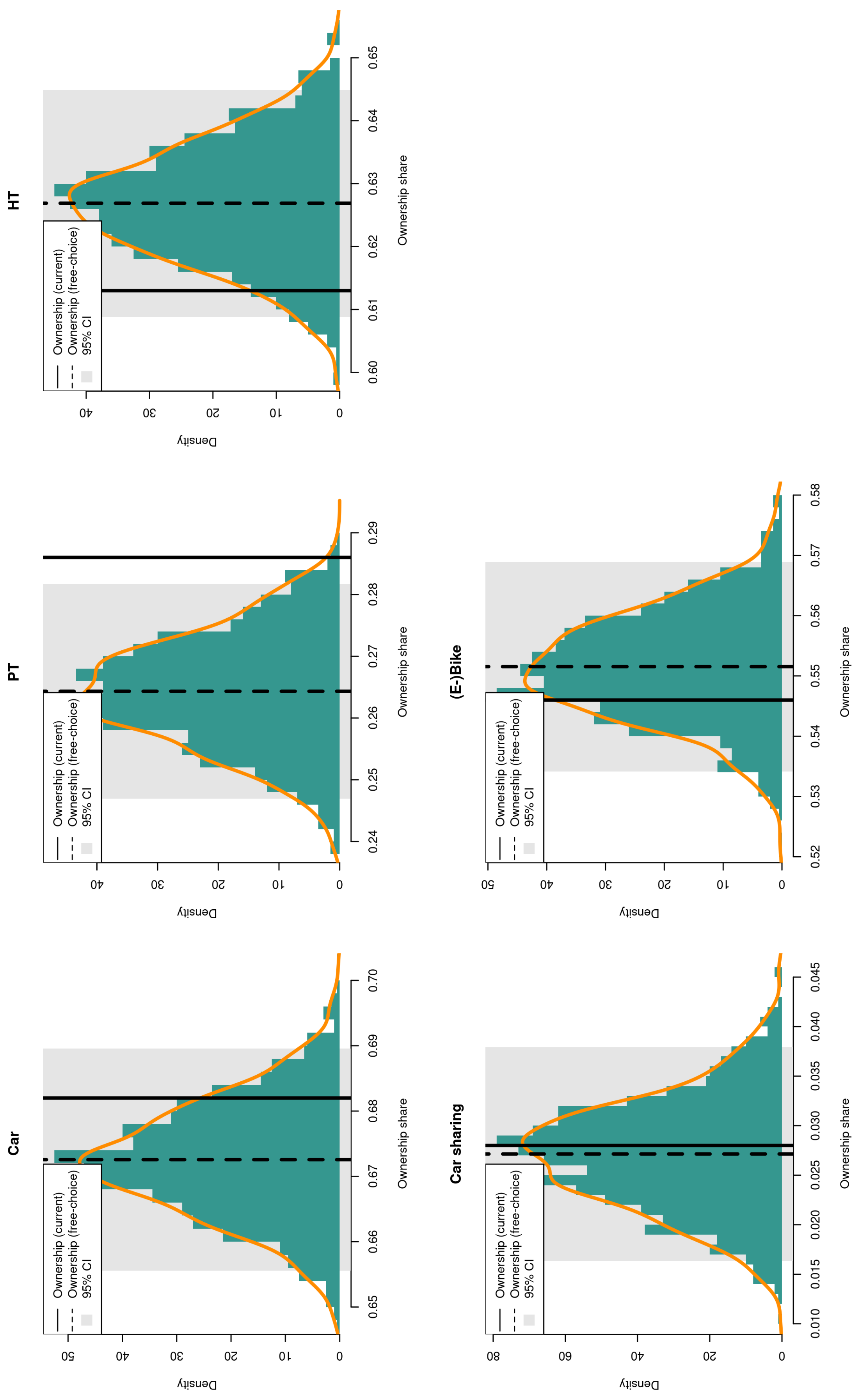
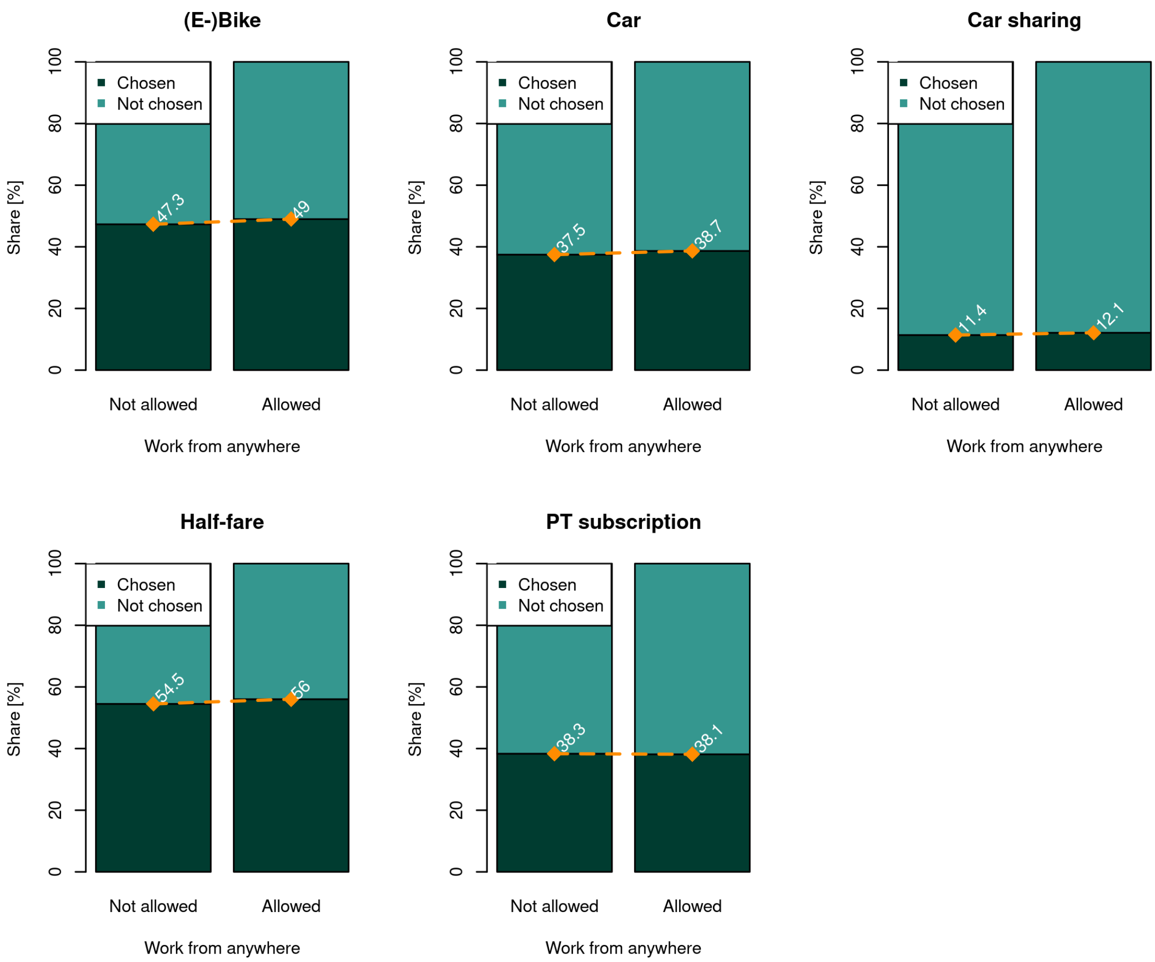


Figure 12: Correlation between work from anywhere and MTO choice.



3.5 Descriptive analysis

Table 6 presents marginal distributions of selected variables for the MZ2021 sample, the pre-study and main study population. The marginals more or less align. In particular, the main sample closely tracks the MZ2021 one with the following exceptions: High-income households are over-represented in the main study (potentially because of less item non-response), as are PT season-ticket owners. Regarding mobility tool ownership, the marginals are not directly comparable because the questions were slightly different: The MZ2021 asks about having access to a tool (without necessarily owning it), while we asked about owning it and using it regularly. Therefore the levels are below the ones of the census. Only the five most frequent NOGA sectors (based on MZ2021 frequencies) are reported here. There, the marginals are quite different. However, a statement about a systematic selection bias (because of the home office topic) cannot readily be made. Whereas it could be argued that *Human Health and Social Work Activities* encompass employees with little possibility to work remotely (and are therefore underrepresented), the same argument could be made for *Manufacturing*. However, there we have a slight over-representation. Lastly, differences in the *Work From Home* distributions are expected as the COVID-19 pandemic still played a role when MZ2021 and the pre-study surveys were fielded. In particular, we observe a shift from very high frequencies to two or three days. Meanwhile, home office access remains at high levels (47%) suggesting that employees who have gained access to the new work form during the pandemic are still (partially) working from home. Working from home on one day a week is the most prominent frequency (14.7%) and for every additional day, the home office share decreases by around two percentage points.

Despite the successful recruitment, a re-weighting scheme was applied to enhance the sample's representativeness further. Based on the above variables, iterative proportional fitting was employed, excluding *Work From Home* and *Mobility Tools* for the reasons outlined before. Separate weight vectors were estimated for the two samples and are applied whenever aggregate statistics are presented.

Fig. 13 highlights the evolution of home office frequency shares throughout the pandemic and compares the status quo to a free-choice scenario. A lot of variation can be observed with the peak of the pandemic (and enforced lockdowns) clearly constituting an edge case with a large share of individuals fully shifting to remote. Still, the shift brought by the pandemic is evident. Surprisingly, the fraction of the population not working from home at all further decreased since the lockdown either due to temporary unemployment (not captured by the survey), new job positions, or changing work policies. From an employee preference perspective, the current situation does not constitute an equilibrium: A large portion would like to increase WFH frequencies, in particular, the population currently not having access.

In Fig. 14 the current home office shares (dark markers) are always the reference. Interestingly, compared to pre-pandemic shares, fewer individuals currently work fully remote. The population with 0 home office days was reduced by roughly 15 percentage points and allocated in particular to $2-3$ days. While this pandemic-induced shift was considerable the second panel suggests, that the desire to work from home is not yet saturated by a wide margin. A big share of people would like to gain home office access potentially reducing the share of employees not working from home from 60% to roughly 30%. The last panel indicates, that while some jobs would allow to go fully remote, only a subset of these people wish to do so. The others prefer a hybrid work scheme.

Table 6: Descriptive statistics: MZ2021 versus pre-study and main samples

		%		
Variable	Value	MZ2021	Pre-study	Main study
Age	18-35	29.4	17.1	27.9
	36-50	36.1	25.7	40.9
	51-65	30.9	56.6	30.5
	65+	3.5	0.7	0.8
Sex	Male	52.7	59.1	52.3
	Female	47.3	40.9	47.7
Married	Yes	50.5	-	50.6
	No	49.5	-	49.4
Nationality	Swiss	75.0	96.2	80.2
	Other	25.0	3.8	19.8
Education	Low	7.2	1.0	4.6
	Medium	45.2	49.7	45.6
	High	47.6	49.3	49.8
Household Size	1	18.8	12.6	16.9
	2	33.7	31.8	35.1
	3	18.6	17.9	17.6
	4+	28.9	37.6	30.4
Household Income	Not reported	15.4	5.4	6.2
	<4’000 CHF	5.5	2.9	4.4
	4’001-8’000 CHF	27.7	21.9	23.0
	8’001-12’000 CHF	26.6	37.2	28.7
	>12’000 CHF	24.7	32.6	37.7
Employment	Full time	60.6	59.8	60.6
	Part time	39.4	40.2	39.4
Work From Home	0	56.6	51.5	53.4
	1	14.3	17.9	14.7
	2	5.9	12.9	12.9
	3	6.5	7.6	9.5
	4	4.3	4.5	5.7
	5+	12.5	5.5	3.9
Noga Sector	Human Health and Social Work Activities	15.5	-	2.9
	Manufacturing	14.6	-	15.2
	Wholesale and Retail Trade	11.2	-	9.9
	Education	8.0	-	4.5
	Professional, Scientific and Technical Activities	9.0	-	9.8
	Other	41.7	-	57.7
Mobility Tools	Car	85.1	88.4	68.2
	Car sharing	6.0	10.8	2.8
	Bike	82.2	82.6	54.6
Season Tickets	National season ticket	9.5	12.5	11.3
	Half-fare card	40.4	63.2	61.3
	Regional season ticket	11.6	8.0	17.3
	None of above	42.8	21.9	21.6

Figure 13: Evolution of the home office frequency share.

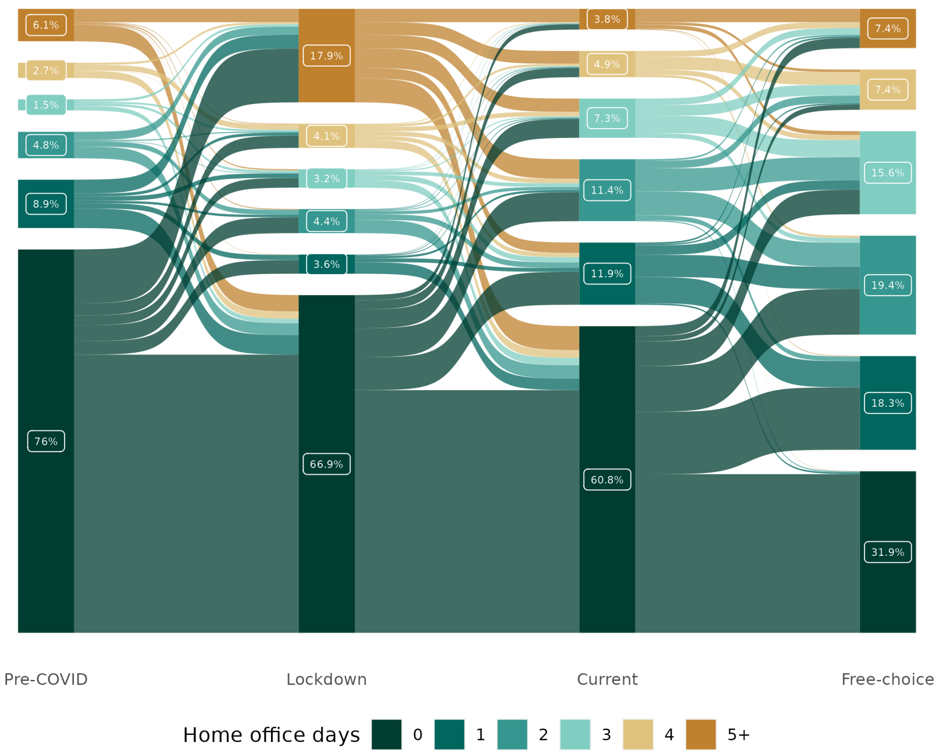
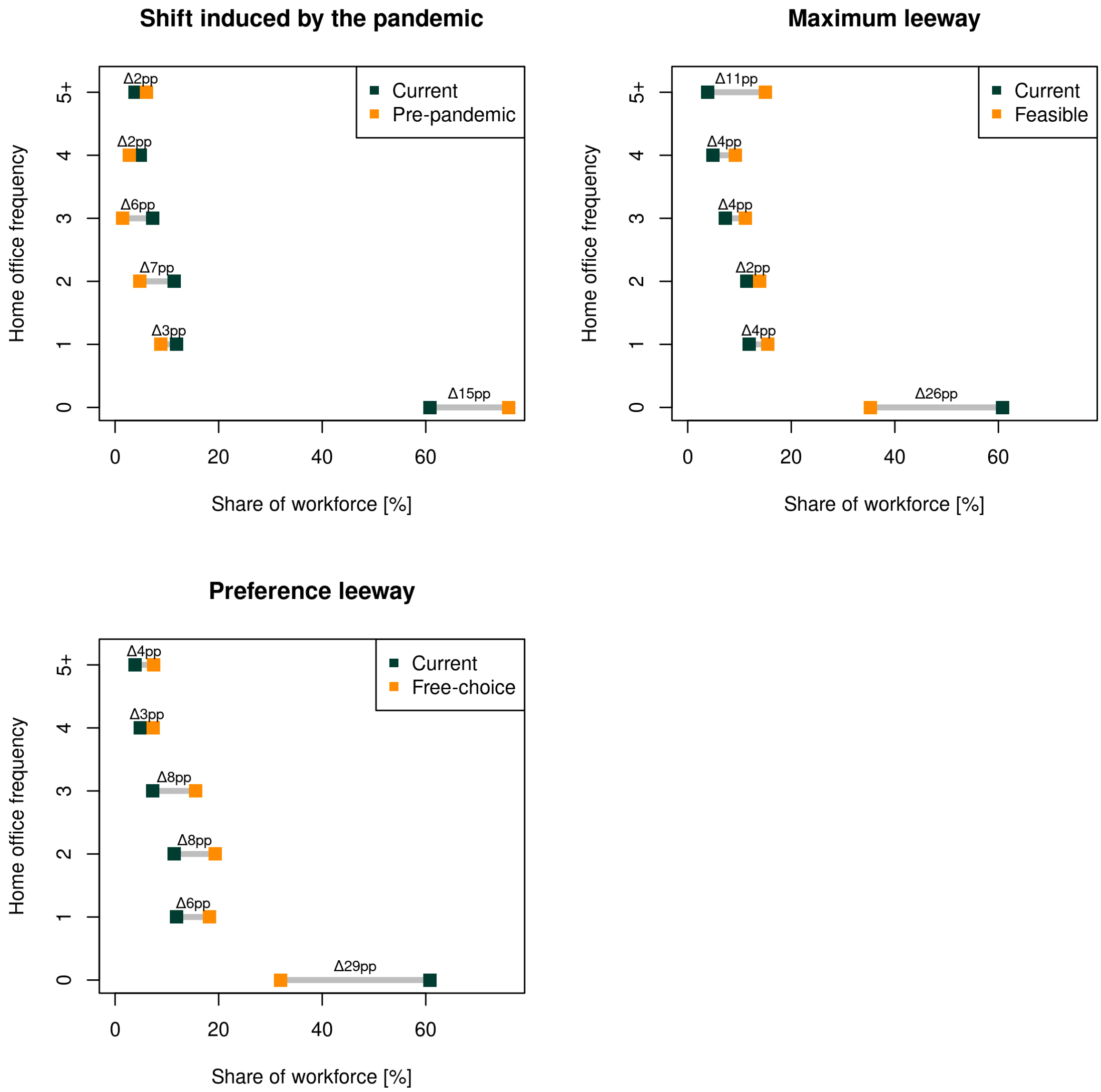


Fig. 15 shows the distribution of current home office shares over the weekdays and separate for full-time and part-time employed. Very different patterns emerge when comparing the two groups as well as the different frequencies. Generally, Mondays and Fridays (corner days) are the preferred weekdays to WFH. If full-time employees have to pick one day, they predominantly choose Friday. Part-time workers on the other hand, choose Monday (potentially already having chosen not to work at all on Fridays). Interestingly, comparing the distributions of two to three-four days WFH for the full-time employed, Monday is only preferred for the population working from home three-four days a week.

We can use this information to simulate the home office share on any given weekday under alternative frequency scenarios: To get an upper bound for home office shares, we compute implied home office weekday shares for the free-choice revealed preference frequencies. The resulting shifts are presented in Fig. 16 and compared to the current distribution.

This puts the shifts observed in Fig. 14 in perspective. There (panel *Preference leeway*) the share of people not working from home would drop from over 60% to almost 30%. As a consequence, the home office share on any given weekday increases substantially:

Figure 14: Induced shifts in home office frequency shares and maximum leeway.



Friday is the upper bound with almost half of the workforce staying at home. Tuesdays and Thursdays still show the lowest shares and transport infrastructure would need to account for these loads. The gap between the days widens under the free-choice scenario with potentially very different network loads over the days (depending on how people adjust their mobility behavior during home office). Therefore, Fridays and Tuesdays to Thursdays should be analyzed separately, when looking at the impact of home office on transport demand.

Having realized the considerable shift in home office and the potential shifts yet to come, we should investigate the consequences for mobility behavior. As a starting point, respondents

Figure 15: Distribution of home office shares over the weekdays by number of days WFH.

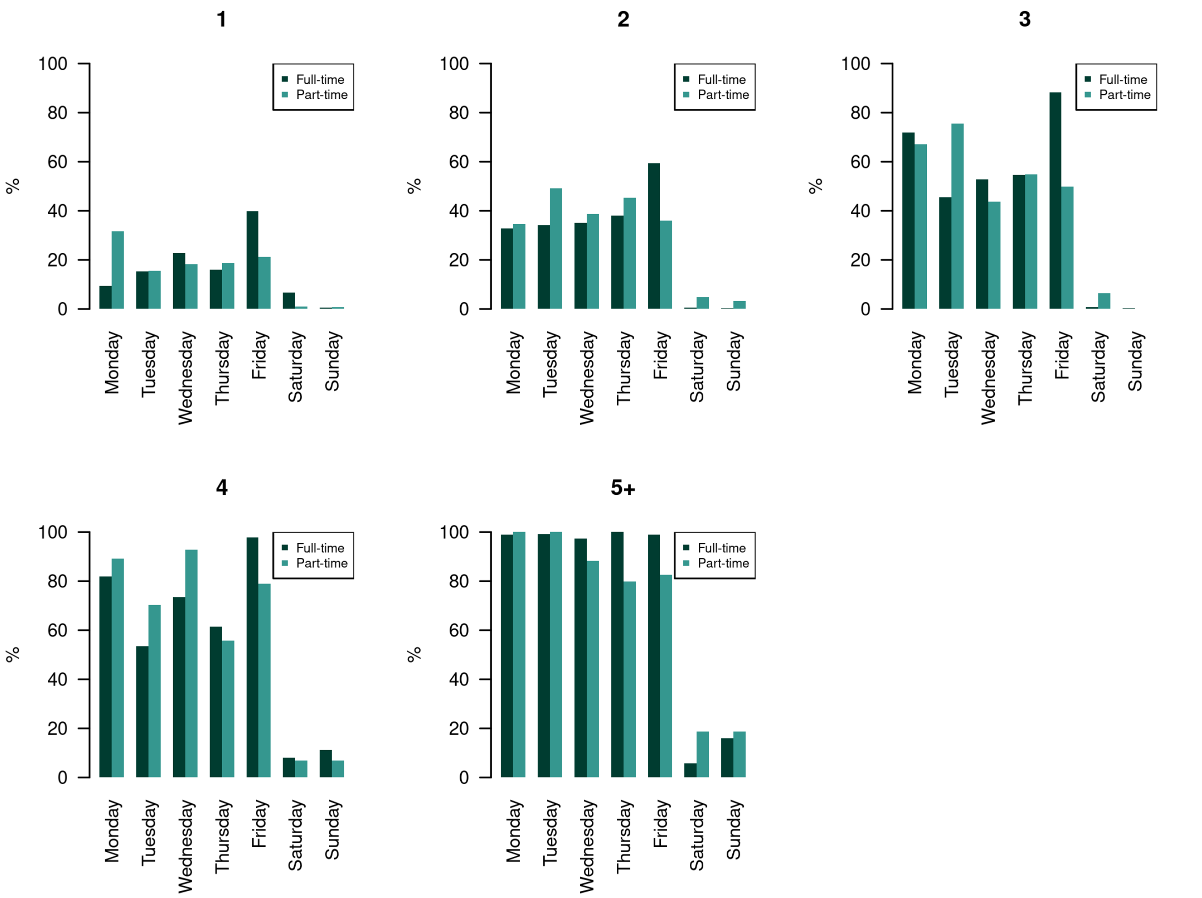


Figure 16: Home office weekday shares: current versus free-choice.

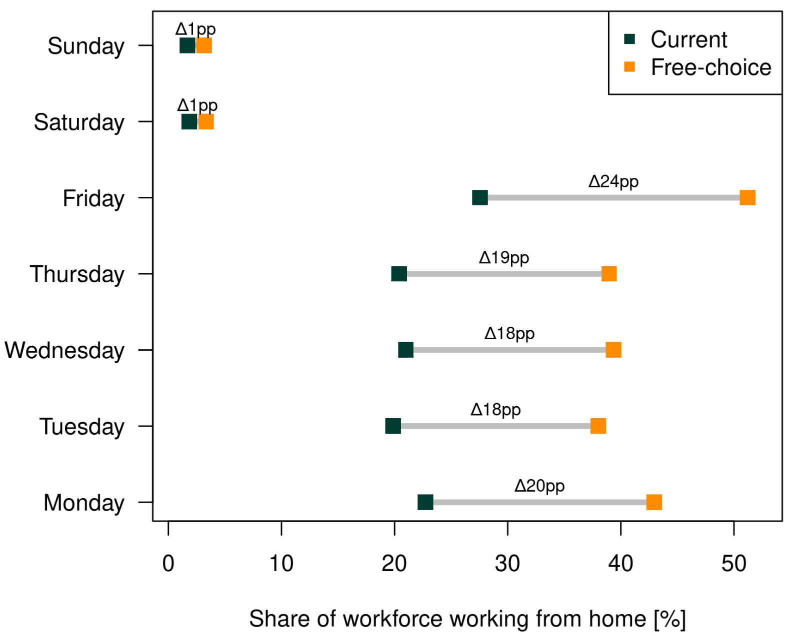
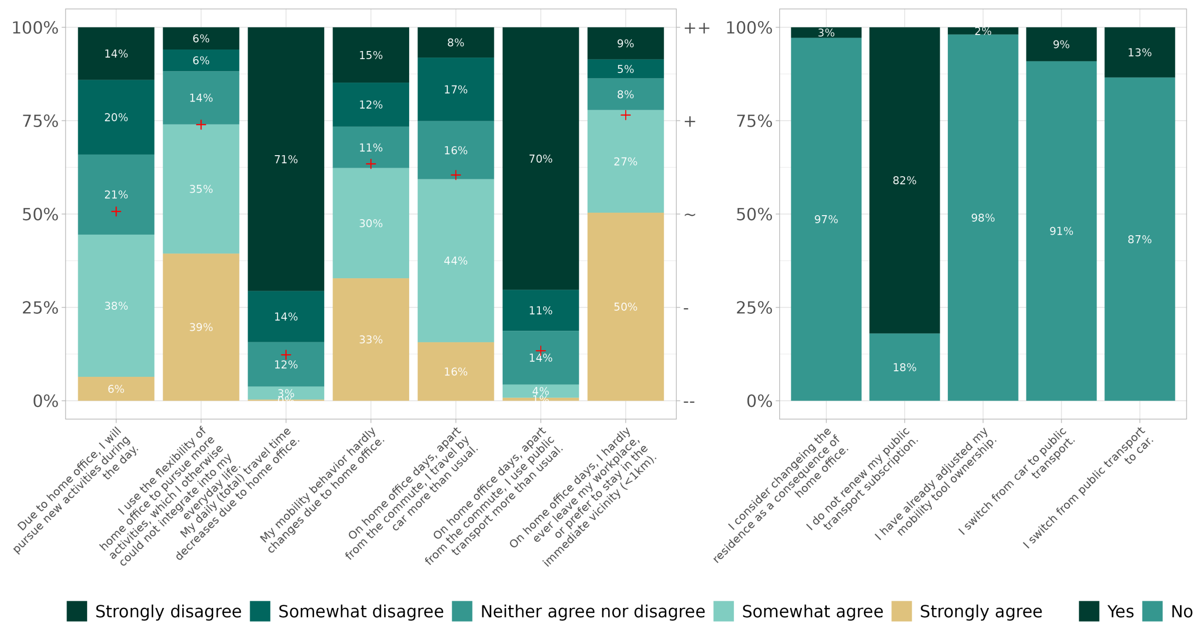


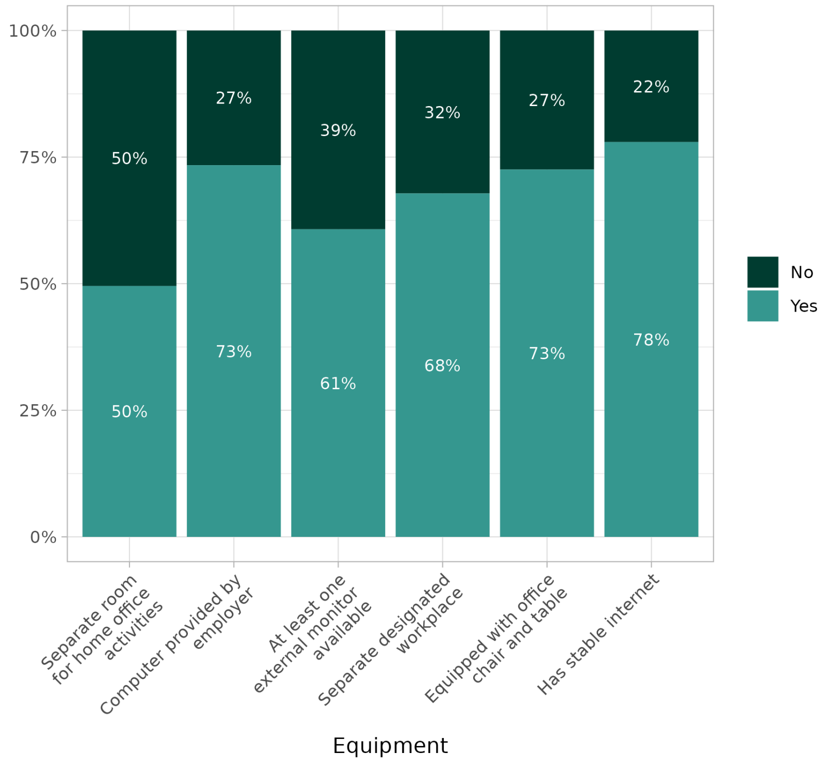
Figure 17: Home office induced change.



were asked to indicate, whether home office induces change in the respective dimension (Fig. 17). People agree that they integrate new activities into their daily schedules on home office days and they do not necessarily travel less. While potentially some additional car trips are generated, PT is used less frequently. Meanwhile, a large share agrees, that they predominantly spend their work hours in close vicinity to their residential environment. The second panel suggests that home office does not induce residential relocation. Further, PT subscriptions are canceled, however, only a few individuals switch from car, strengthening the insights derived from the average treatment effects (Section 3.4). Some individuals no longer need a car leaving net effects for mobility tool ownership ambiguous (slightly in favor of more car ownership).

The quality of the home office environment is reflected in Fig. 18, with good working conditions for a majority of the people. However, half of the population has no designated room for work activities and a third has no reserved workplace. Distraction from other household members as well as working from the kitchen table are still frequent scenarios (around one-third of the cases).

Figure 18: Home office equipment.



3.6 Teleworkability factor analysis

Not every job can be performed remotely. And even if a job is suitable for home office, not all work tasks can be shifted to remote. We label this varying degree to which a job is feasible for home office as *teleworkability*. To assess an individual's teleworkability, an item battery of six Likert-style questions was proposed. In this section, the result of an exploratory and confirmatory factor analysis (EFA and CFA) is presented to gauge the suitability of the indicators to capture this latent dimension.

The EFA hinted that two latent variables explain the choices on the Likert scale, cumulatively explaining 53% of the variation. One factor describes job-related dimensions whereas the other is concerned with the personal characteristics as well as the (home office) environment of that person. The two factors could thus be labeled *in-job* and *out-job*.

The CFA confirms that the two-factor model performs better than the one-factor model across all fit indicators. The comparative fit index (CFI) and Tucker-Lewis index (TLI)

Table 7: Confirmatory factor analysis

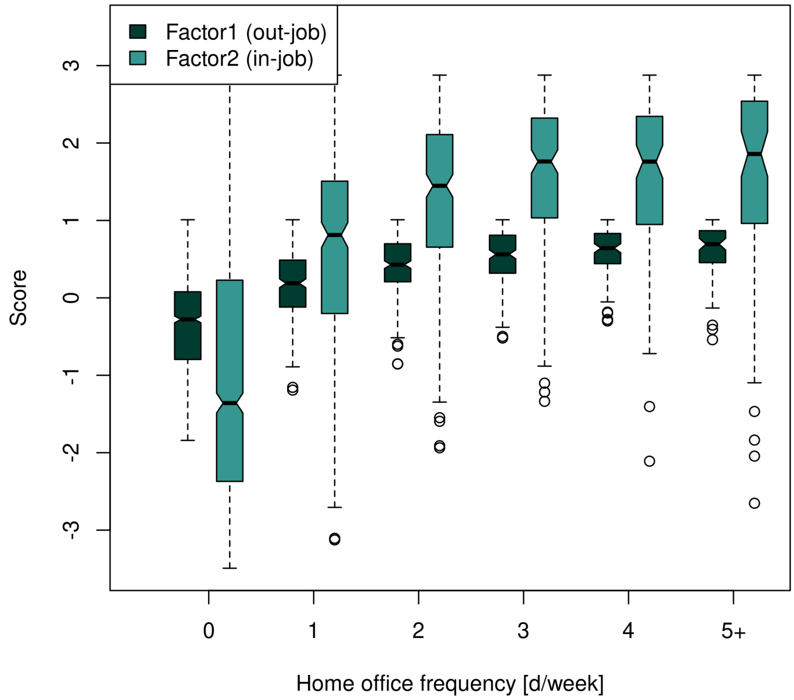
	One Factor Model	Two Factor Model
F1: I am tech savy	1.00	1.00
	(0.00)	(0.00)
F1: you as a person	1.54^{***}	1.94^{***}
	(0.08)	(0.10)
F1: workstation	1.41^{***}	1.77^{***}
	(0.08)	(0.09)
F1: job can be done from computer	2.69^{***}	
	(0.13)	
F1: job requires physical interaction	-1.54^{***}	
	(0.09)	
F1: job requires specific work environment	-1.99^{***}	
	(0.10)	
F2: job can be done from computer		1.00
		(0.00)
F2: job requires physical interaction		-0.59^{***}
		(0.03)
F2: job requires specific work environment		-0.76^{***}
		(0.03)
Nu. obs.	1914	1914
Nu. params.	12.00	13.00
CFI	0.82	0.94
TLI	0.70	0.89
RMSE	0.18	0.11
LL	−22424	−22229
AIC	44872	44484
BIC	44939	44556

Note: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

imply good fit whereas the root mean squared error of approximation implies mediocre fit. Still, the one-factor model can be used to gauge the relative importance of all the indicators (as the two-factor model has two normalized loadings). Unsurprisingly, the possibility to perform a job on a computer loads most strongly on the overall teleworkability. Meanwhile job-related and person-specific indicators load with similar magnitudes.

The signs of the factor loadings are intuitive and the loadings itself highly significant. The two factors are correlated hinting that people with a higher in-job teleworkability have higher out-job teleworkability, e.g. they are equipped with a more suitable home office workstation.

Figure 19: Correlation between factors and home office frequency.



Both factors seem to discriminate people who do not work remotely and people who do (Fig. 19). On the other hand, teleworkability seems not to be different for employees working three, four or five-plus days from home a week. Going fully remote is therefore most likely not purely a question of teleworkability but other factors (such as the preference dimension) could play a dominant role.

We propose accounting for this latent teleworkability in modeling approaches, acknowledging that not every employee has the full choice set.

3.7 Summary and conclusion

This study details the survey work to investigate and model home office access and frequency. While the literature on understanding drivers of home office adoption is large, work arrangement characteristics are usually not considered. Meanwhile, the surging share of teleworkers as a consequence of the pandemic, makes it likely, that hybrid work policies no longer can be negotiated at the bilateral level. The proposed stated preference experiment allows researchers to investigate, whether reasonable incentive schemes can have leverage (and should thus be considered when modeling) or whether employees' preferences and employers' hard constraints play a dominant role.

Further, the data collected is tailored to elicit the rebalancing of mobility tool portfolios as a consequence of WFH. Some mobility tools depreciate slowly. Therefore purchase decisions are only observed irregularly and usually not simultaneously. Hence, it is difficult to understand the nuanced trade-offs between mobility tools. Our work elaborates on difficulties encountered when designing an SP experiment in that context. We propose an abstraction that emphasizes the *between mobility tool* trade-off (emphasizing the availability of a certain tool rather than its specifics). Meanwhile, *within mobility tool* preferences (for characteristics of a given tool) can still be studied over multiple choice observations as we argue.

The data collected in this work therefore allows researchers to investigate the following research questions: What are the preferences for hybrid work arrangement characteristics? In how far do they impact adoption and the frequency choice? Are they of relevance, compared to other factors (such as socio-demographic and job-task-related attributes)? How do teleworkers rebalance their mobility tool portfolio, in light of such hybrid work arrangements?

The proposed attributes and levels in the SPs were carefully selected to define meaningful trade-offs. For the WFH-SP a pre-study was fielded with the primary purpose to identify attributes of relevance in the decision-making process. For the MTO-SP a python package was written to scrape specifics of the current Swiss car fleet, allowing us to be precise about the underlying cost assumptions of owning a car.

Investigating the choice variation, we find that $2-3$ home office days is the preferred option. Meanwhile, the distribution of the differences (observed choice minus free, unconstrained choice) is symmetrical around 0: In the absence of any (dis-) incentives, respondents choose the free-choice frequency, while any deviation from it must be attributed to the applicable work arrangement conditions.

The computation of home office treatment effects elicits the relevance for mobility tool ownership: We find a significant negative treatment effect for car (-1.4pp decrease in ownership share per additional home office day) and PT subscriptions (-3.1pp) and a significant positive effect for HT (2pp, suggesting a substitution effect from PT subscriptions). Meanwhile, car sharing and (E-) bike ownership seem not affected.

Our study population is representative of the German-speaking part of Switzerland and it is thus valid to generalize sample averages. We observe a shift from very high home office frequencies (during the pandemic) to two or three days (after the pandemic). Meanwhile, home office access remains at high levels (47%) suggesting that employees who have gained access to the new work form during the pandemic are still (partially) working from home. From an employee preference perspective, the current situation does not constitute an equilibrium: A large portion would like to increase WFH frequencies, in particular, the population currently not having access (potentially reducing the share not working from home to roughly 30%).

Generally, Mondays and Fridays are the preferred weekdays to WFH. We compute the population share working from home on any given weekday and under alternative frequency scenarios. The previously alluded potential shift yet to come has considerable leverage, increasing the home office share across weekdays substantially. Friday is the upper bound with almost half of the workforce staying at home. Tuesdays and Thursdays still show the lowest shares and transport infrastructure would need to account for these loads. The gap between the days widens under the free-choice scenario with potentially very different network loads over the days. Therefore, Fridays and Tuesdays to Thursdays should be analyzed separately, when looking at the impact of home office on transport demand. This also highlights that an understanding of what constrains this free-choice (such as hybrid work policies) matters.

Home office has potentially a profound effect on daily activity schedules. A large share agrees, that they predominantly spend their work hours in close vicinity to their residential environment when working from home. This shift from downtown to residential neighborhoods could induce people to relocate. However, the survey answers suggest, that home office does not necessarily stimulate relocation. We further find, that half of the population has no designated room for work activities and a third has no reserved workplace. Distraction from other household members as well as working from the kitchen table are still frequent scenarios.

We introduce the notion of *teleworkability* and propose an item battery of Likert-scale questions to account for the varying degree to which a job is feasible for home office. Factor analysis suggests two latent variables: One factor describes job-related dimensions whereas the other is concerned with the personal characteristics as well as the (home office) environment. Both factors seem to discriminate the people who do not work remotely and people who do. On the other hand, teleworkability seems not to be different for employees working three, four, or five-plus days from home a week. Going fully remote is therefore most likely not purely a question of teleworkability but other factors (such as personal preferences) could play a dominant role. We propose accounting for this latent teleworkability in modeling approaches, acknowledging that not everyone has the full choice set.

4 Econometric models for the MATSim case study

4.1 Introduction and motivation

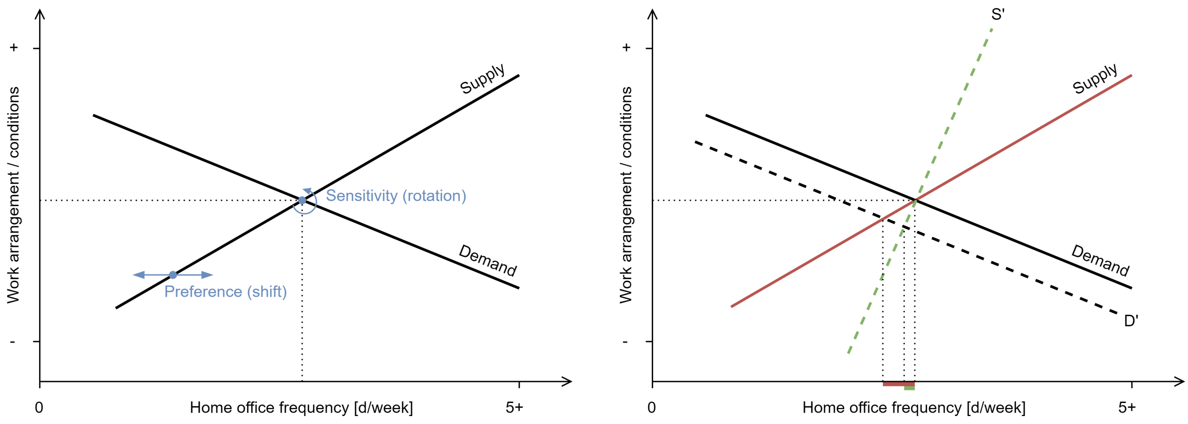
The goal of this chapter is to introduce the econometric models employed in the MATSim simulations. As already explained in Section 3 three key dimensions of individual decision-making and behavior impact the transport equilibrium: 1. The home office access and frequency, 2. Alternative activity chains, 3. Alternative mobility tool ownership. By *alternative* we mean home office induced changes. While we propose econometric models for 1. and 3., activity chains will be tackled with help of heuristic scenarios and statistical matching (where we use tracking data from the TimeUse+ study to infer realistic daily plans).

The analysis in Section 3.4 already hinted that treatment effects exist for MTO. The modeling ambition is therefore straightforward: Try to explain MTO as well as possible while incorporating the treatment effects in the statistical model. We are interested in getting unbiased estimates (especially for the home office frequency sensitivities), but we must remember that the main goal is to get a realistic distribution (i.e., of WFH access and frequency and MTO) over the synthetic MATSim population. In some sense, correlation is therefore more important than causation: For example, we are not interested in whether it is higher education or higher income (two correlated variables) that assigns a higher probability of PT subscription ownership to the individual. If we didn't control for income levels, its effect would partially be attributed to education, overestimating the impact of education on PT subscription ownership. However, this is not necessarily a problem for prediction (as long as the biased variable is not the policy variable of interest).

Modeling WFH is complex for several reasons: First (and technically), WFH has two dimensions - WFH access and WFH frequency. Therefore, a natural selection process is inherent (where the latter is only observed conditional on the first). Second, the observed frequency results from a market equilibrium, where the employees and employers interact and negotiate. In principle, both the supply and demand sides should be modeled simultaneously; otherwise, we have the classical endogeneity bias through simultaneity.[9] Now, in the WFH-SP, the experiment exactly (exogenously) described the hybrid work arrangement conditions (employer perspective - the demand side in labor economics). In

[9]The classical example is estimating market clearing conditions, i.e. the relation between price and quantity

Figure 20: Home office labor market clearing under different sensitivity scenarios.



other words, the demand is exogenously given.

Let us illustrate the home office labor market with a classical supply and demand diagram (Fig. 20): The steeper the supply curve, the less sensitive employees are to average WFH conditions. At the extreme, a vertical curve means that employees always supply the same WFH frequency. Similarly, the steeper the supply curve, the less the demand (employer perspective) matters. Again, in the case of vertical supply, the location of the demand curve has no effect. On the other hand, a flat supply curve implies that small shifts in the demand curve result in large changes in aggregate telework frequencies. This means for our analysis the following: If we should find small elasticities to the proposed WFH-SP attributes (steep supply curve), understanding the demand is less crucial, i.e. there is not much benefit in understanding when exactly employers propose certain hybrid work policies.

4.2 Methodology

We are now introducing three modeling methods to estimate discrete outcomes: Multinomial logistic regression (MNL), ordered logistic regression (OR), and ordered probit regression (OP). The latter two only differ from one another in terms of the link function applied (logistic function versus the cumulative normal) and usually yield very similar results. All three methods are conceptually similar in the sense that they model a latent variable and observed choices are then linked to this latent scale. The methodological key difference between the MNL and OL/OP is, that the latter two only have one latent scale, and the ordinal choices are discriminated by segmenting that latent scale. On the other hand, the MNL allows for different utility functional forms, for each alternative separately. In contrast, in the OL/OP models, we only estimate one coefficient per attribute. This coefficient then increases or decreases the latent propensity and depending on whether or not the next segmentation threshold (cutoff parameter) is reached, reveals another choice.

Since we are estimating on pooled data (i.e., linking RP and SP data sources) we have to correct for differences in scale. The latent variable is unitless and therefore one parameter has to be normalized. This is usually (and implicitly) the error variance which is fixed to 1 (alternatively, one could also fix one of the cutoff parameters in the OL, OP model). However, given a model specification, the error variance for two different data sources is not necessarily the same. Therefore an additional scale correction term has to be estimated.

4.2.1 Multinomial logistic regression

We now describe the modeling frameworks separately, starting with the MNL: Let's recall that each decision maker n was asked to choose between two alternatives j (work arrangements in our case) in choice scenario t. The decision maker maximizes utility of the form $U_{njt} = V_{njt} + \varepsilon_{njt}$, where V_{njt} is the observed part of utility and ε_{njt} represents unobserved factors which follow a Gumbel (type I extreme value) distribution. The modeler assumes that V_{njt} can be expressed as $X_{njt}\beta$. It can be shown that the probability of observing decision maker n choosing alternative j in choice occasion t is (Train, 2009):

$$P_{njt} = \frac{\exp X_{njt}\beta}{\sum_j \exp X_{njt}\beta} \tag{1}$$

The resulting likelihood can now be written as:

$$L(\beta) = \prod_{n}^{N} \prod_{i}^{I} \prod_{t}^{T_n} (P_{nit})^{y_{nit}} \tag{2}$$

where N is the total sample of decision makers, T_n the individual-specific total number of choice tasks, and I the number of alternatives (in our case two proposed work arrangements). $y_{nit} = 1$ if person n chooses i and zero otherwise. However, computationally it is beneficial to remove the product operators by taking logs:

$$LL(\beta) = \sum_{n}^{N} \sum_{i}^{I} \sum_{t}^{T_n} y_{nit} \log P_{nit} \tag{3}$$

The model is estimated in *R* (R Core Team, 2023), using the *mixl* package (Molloy *et al.*, 2021a).

4.2.2 Ordinal regression

Let us introduce the ordinal logistic regression (proportional odds) model (see e.g. Train, 2009): Let the latent variable be incompletely measured and a function of observed attributes $y^*_{nt} = X_{nt}\beta + \varepsilon_{nt}$. Then we observe the choice $y_{nt} = k$ according to:

$$y_{nt} = \begin{cases} 0 & \text{if } -\infty < y^*_{nt} \leq \tau_0 \\ 1 & \text{if } \tau_0 < y^*_{nt} \leq \tau_1 \\ \vdots & \\ 5+ & \text{if } \tau_4 < y^*_{nt} \leq +\infty \end{cases} \tag{4}$$

This yields the following probability:

$$P_{nkt} = P(y_{nt} = k|X_{nt}) = P(\tau_{k-1} < y^*_{nt} \leq \tau_k) \tag{5}$$
$$= P(\tau_{k-1} < X_{nt}\beta + \varepsilon_{nt} \leq \tau_k) \tag{6}$$
$$= \frac{1}{1 + \exp \tau_k - X_{nt}\beta} - \frac{1}{1 + \exp \tau_{k-1} - X_{nt}\beta} \tag{7}$$

where we have assumed a logistic error distribution. If we assume a normal distribution for the error term, then the link function would change and the probability in Eq. (6) can be expressed as:

$$P_{nkt} = \Phi(\tau_k - X_{nt}\beta) - \Phi(\tau_{k-1} - X_{nt}\beta) \tag{8}$$

The likelihood of a single choice observation for individual n at occasion t can then be written as:

$$L(\beta, \tau) = \prod_{k=1}^{K} (P_{nkt})^{y_{nkt}} \tag{9}$$

where $y_{nkt} = 1$ if $y = k$ was observed and zero otherwise. As before, we take the logarithm after having marginalized over all N decision makers and all T_n choice occasions to arrive at:

$$LL(\beta, \tau) = \sum_{n}^{N} \sum_{t}^{T_n} \sum_{k}^{K} y_{nkt} \log P_{nkt} \tag{10}$$

We use the *MASS* (Venables and Ripley, 2002) (OL) and *apollo* (Hess and Palma, 2024) (OP) to specify our models with ordered outcomes.

As there is currently no implementation of Heckman-type selection models in R[10] (e.g., for modeling the joint probability of having home office access and choosing to work from home on n days a week) we use random error components to introduce correlation between the two outcomes (see e.g. Train, 2009, p. 139). Let us slightly rewrite the latent propensity as:

$$y_{nt}^{(i)*} = X_{nt}^{(i)}\beta^{(i)} + \underbrace{\eta_{nt}^{(i)}}_{\mu_{nt}\gamma^{(i)}+\varepsilon_{nt}^{(i)}} \tag{11}$$

where the i indicates a model component and μ and ε are standard normally distributed. Two components i might now share unobserved factors that influence both propensities μ_{nt} and thus introduce error correlation.

4.2.3 Goodness of fit indicators

In all the subsequent tables we report goodness of fit indicators. The benchmark *Null model* is the equal shares model which is a model without any information content apart from the number of alternatives considered. The *McFadden R2* then compares the final log-likelihood to the one of the Null model: $1 - \frac{\text{LL(final)}}{\text{LL(null)}}$. The value can range between 0 and 1 and values closer to 1 indicate better performance compared to the Null model. It is important to acknowledge that the Null model performs better if choice shares are evenly distributed.[11]

Further, marginal probability effects (MPE) are computed and reflect the change in choice probability either compared to the reference level of a particular variable or compared to an increase of 10% for continuous variables. On an aggregate level, this reflects expected changes in market shares. For the WFH frequency implied changes in average home office days supplied are reported.

[10]The *sampleSelection* package does only allow for continuous outcomes.
[11]For example, if there are only two possible outcomes and the observed choices are evenly distributed, then the Null model predicts right with a probability of 50%. The likelihood contribution is then $\log 0.5$ for each choice observation.

4.2.4 Calibration of the constants

In all the models, the main task of the modeler is to specify the relation between observed variables and the latent utility/propensity. We selected the models based on conventional goodness of fit indicators (log-likelihood, AIC, BIC). Insignificant variables were only sporadically removed as dropping variables attribute the effect to correlated variables and therefore bias the estimates.

As already alluded, a constant is usually included in a model to capture the average effect of unobserved factors. In forecasting, it is often a good idea to adjust these constants to match observed market shares. An iterative process as described in Train (2009) is used to recalibrate the constants of the WFH model for the MATSim simulation.[12] Let α_j^0 be the jth estimated threshold in an OP model. Let S_j denote the share of decision makers that choose discrete outcome j. Using the OP model with its original values of $\alpha_j^0 \; \forall j$, predict the share of decision-makers in the forecast area who will choose j. Label these predicitons $\hat{S}_j^0 \; \forall j$. Compare the predicted shares to the actual shares and adjust the threshold parameters α_j in the next iteration according to:

$$\alpha_j^1 = \alpha_j^0 + \ln S_j / \hat{S}_j^0. \tag{12}$$

Repeat this process until the forecasted shares are sufficiently close to the real ones (we used a threshold value of 1pp).

We first reweighted the survey population to match the Zurich population (based on the weighted MZ2021) and computed ground truth home office access and frequency shares. We then calibrated the model applied to the synthetic population as described above (first calibrating the threshold for the access component and then the thresholds for the frequency component with the calibrated selection threshold).

[12]The MTO models were not recalibrated since the resulting mode shares (usually the target in the calibration) already matched reasonably well and MTO only indirectly affects mode shares.

4.3 Hybrid work arrangement choices and its implications for home office frequencies

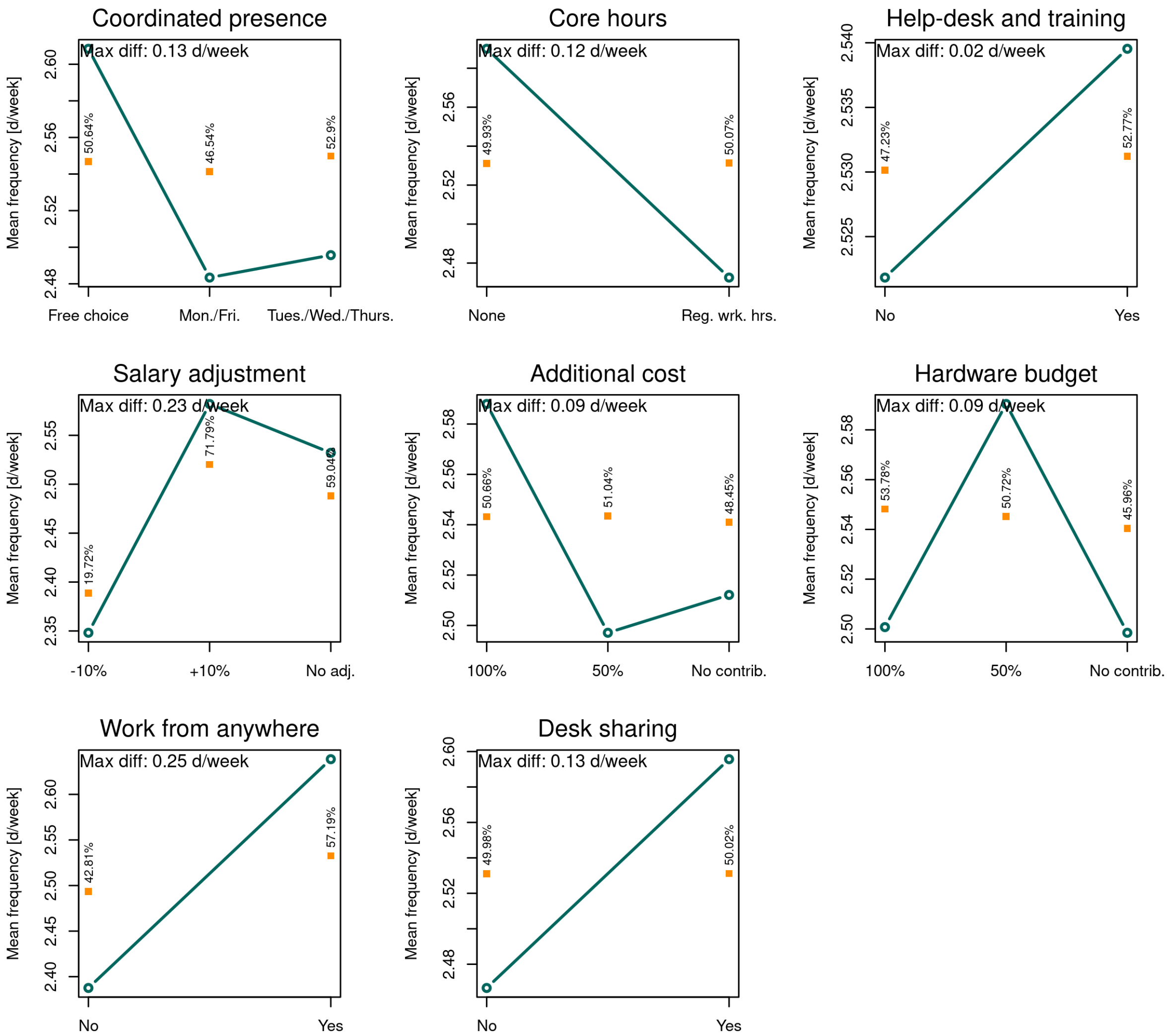
Fig. 21 shows mean effects for the eight proposed attributes and their respective levels. The maximum difference can be read as a first indication of the elasticity effect. Simultaneously, we plotted how often an arrangement was chosen, if a certain attribute level was presented (orange markers, separate scale). On the one hand, this proxies preferences for the work arrangement choice, on the other hand, it also highlights that we still have sufficient variation in the frequency choice. Only the two attributes *salary adjustment* and *work from anywhere* show obvious and intuitive patterns in that regard. Still, in almost 20% of the choice situations, a salary deduction (of 10%) was accepted. For the mean frequencies (lines) all the effects are meaningful except for *hardware budget*, where a 50% participation has a stronger positive effect than full participation. However, the maximum difference is very small (in fact, the kink is exaggerated by the scale of the y-axis). Concerning expected elasticity effects (Max diff.), again, *salary adjustment* and *work from anywhere* show the biggest difference. Salary deductions yield stronger effects than salary increases. Interestingly, *additional cost* only seems to have an effect if the employer fully carries them. Again, the maximum difference is though very small.

The estimation results of the MNL model are presented in Table 8, where conventional metrics are reported (i.e., estimates of the coefficients, robust standard errors and p-values as well as resulting significance levels along goodness of fit indicators). Again, the MPE is the change in choice probability, attributed to a single variable and in comparison to its reference level and under the ceteris paribus assumption.

Overall, the results are intuitive with the expected signs. All attributes were found to be significant except for *core hours* and *desk sharing*. However, as we will see, *desk sharing* plays a role in the frequency choice.

There are three monetary attributes (*salary adjustments, additional cost* and *hardware budget*) all implying a utility equivalent of a marginal monetary unit. However, the marginal Swiss franc seems to be valued differently depending on the reason it was received/spent. There might be an argument on the grounds of what employees deem fair (or unfair), necessary (or unnecessary) as monetary compensation for their home office efforts: The connection between having to buy a second desktop monitor is much more evident than having an increased bill at the end of the month for the additional energy consumed by that particular second display. Decreasing the salary yields a stronger

Figure 21: Aggregate home office supply plotted against SP attributes.



negative effect than increasing it by the same percentage amount.

Commenting on effect size (marginal probability effects) the *salary adjustments* play the most substantial role followed by *work from anywhere*. Expressed in salary adjustment equivalents, the option to telework from anywhere roughly corresponds to a salary increase of 4% on home office days ($\frac{\beta_{\text{work from anywhere}}}{\beta_{\text{salary adjustments}}}/20$).

Last, coordinating office presence on Mondays and Fridays reduces the attractiveness of the work arrangement. This is in line with the home office distribution over the weekdays as reported in Section 3.5, where we observe a higher telework supply on these days.

Table 8: Estimation results: Multinomial logistic regression

Coef.	Level	Estimate	Std. Error	p-Value	Sig.	MPE [pp]
ASC		0.038	0.054	0.486		
Coordinated presence	Monday/Friday	-0.202	0.075	0.007	**	-3.542
	Tuesday-Thursday	-0.158	0.082	0.054		-2.731
Core hours	Regular working hours	0.028	0.056	0.616		0.489
Help-desk and training	Yes	0.219	0.053	0.000	***	3.816
Salary adjustment	No salary adjustment	1.355	0.088	0.000	***	23.667
	+10%	1.788	0.102	0.000	***	33.389
Additional cost	50% participation	0.197	0.072	0.006	**	3.417
	100% participation	0.158	0.079	0.045	*	2.772
Hardware budget	50% of necessary expenses	0.178	0.076	0.018	*	3.107
	100% of necessary expenses	0.335	0.078	0.000	***	5.819
Work from anywhere	Allowed	0.440	0.059	0.000	***	7.699
Desk sharing	Yes	-0.055	0.060	0.354		-0.966
GOF indicators:						
N respondents	636					
N choice observations	2037					
N parameters	13					
LL(null)	-1411.941					
LL(final)	-1070.084					
McFadden R2	0.242					

Note: *5%, **1%, ***0.1%

Now the implications of hybrid work arrangement attributes for home office frequencies are discussed. The reported elasticity effects are interpreted in the following way: Take for example a salary adjustment of +10%. The corresponding elasticity reads 0.203 which implies that compared to the reference level (here a salary deduction of −10%), aggregate weekly home office supply would increase by roughly 0.2 days per week.

Again, the results mostly align with intuition. However, this time, fewer attributes seem to govern the frequency choice. As before *core hours* does not influence behavior significantly. In addition *help-desk and training* as well as *hardware budget* are not found to be significant. In contrast, *desk sharing* now has a slight positive effect, meaning that employees tend to increase home office supply if the employer establishes shared office spaces.

The attributes of most substance are again *salary adjustments* and *work from anywhere*. Interestingly, the elasticity of *work from anywhere* is now comparable in magnitude which was not the case for the MPE in the work arrangement choice.

For a more nuanced discussion of the model results, the reader can consult Heimgartner and Axhausen (2024). The main conclusion is that resulting elasticity effects make it unlikely that large variations in telework frequencies can be attributed to work policies.

Table 9: Estimation results: Ordered logistic regression

Coef.	Level	Estimate	Std. Error	p-Value	Sig.	Elast. [d]
Coordinated presence	Monday/Friday	-0.112	0.105	0.286		-0.047
	Tuesday-Thursday	-0.223	0.104	0.031	*	-0.093
Core hours	Regular working hours	0.003	0.085	0.974		0.001
Help-desk and training	Yes	0.007	0.085	0.930		0.003
Salary adjustment	No salary adjustment	0.324	0.140	0.021	*	0.135
	+10%	0.485	0.136	0.000	***	0.203
Additional cost	50% participation	0.069	0.103	0.506		0.029
	100% participation	0.238	0.104	0.022	*	0.099
Hardware budget	50% of necessary expenses	0.127	0.105	0.226		0.053
	100% of necessary expenses	0.084	0.107	0.434		0.035
Work from anywhere	Allowed	0.416	0.086	0.000	***	0.174
Desk sharing	Yes	0.172	0.084	0.041	*	0.072
Free-choice	1 day	1.270	0.173	0.000	***	0.515
	2 days	2.388	0.173	0.000	***	0.973
	3 days	3.648	0.189	0.000	***	1.510
	4 days	4.820	0.207	0.000	***	2.020
	5+ days	6.509	0.256	0.000	***	2.743
Cutoff	0|1	-1.283	0.256	0.000	***	
	1|2	1.116	0.237	0.000	***	
	2|3	3.599	0.253	0.000	***	
	3|4	5.855	0.269	0.000	***	
	4|5+	7.989	0.298	0.000	***	
GOF indicators:						
N respondents	636					
N choice observations	2037					
N parameters	22					
LL(null)	-3649.814					
LL(final)	-2438.722					
McFadden R2	0.332					

Note: *5%, **1%, ***0.1%

In other words, it is difficult to incentivize employees to do more or less home office (i.e., the supply curve of Fig. 20 is steep). This might explain why leaders take a firm stance and essentially demand employees back to the office. On the other hand, the results emphasize, that employees value home office greatly (that's what makes sticks and carrots not effective). Home office frequency is most likely negotiated as part of the work arrangement and not a result of the agreed (home office) conditions. Market dynamics (economic business cycles) could play a pivotal role in determining which side has larger leverage.

This implies for our simulation study, that there is not much value in designing scenarios with varying work arrangement characteristics. We therefore abstract from it and focus on scenarios with alternative activity patterns as will be explained in Section 5.5.

4.4 Econometric models for the MATSim integration

The next sections introduce the models used for the MATSim integration. Concretely, they are used to predict home office access and frequency as well as mobility tool ownership for the synthetic population underlying the MATSim scenario. As such, the main purpose is to get realistic population distributions and causal inference is secondary. For example, we already acknowledge that resulting home office frequencies are a market equilibrium and co-determined by demand and supply. In the absence of very rich data about the employer, (as is the case here) omitted variable bias is almost guaranteed. For example, higher educated people might tend to work for employers who generally support home office and we would need to somehow control for this propensity. If we do not, the effect is wrongly attributed to the education level (which in the presented scenario would upward bias the estimate). However, the only thing we are interested in is placing highly educated individuals with a higher probability in the population doing more home office. Why exactly they are placed in this group does not matter. The reader should keep this in mind and be careful about the causal interpretation of the model coefficients.

In the tables that follow, only significant values are presented in order not to overwhelm the reader. However, as explained in Section 4.2 most of the insignificant variables were kept in the model specification (the final number of parameters retained is reported as part of the goodness of fit indicators). In the following discussion, we will not detail every single coefficient but try to highlight key points.

4.4.1 WFH model

The results of the Heckman selection model are presented in Table 10. The *selection model* reflects whether or not an individual has the possibility to do home office at all (home office access) and the *frequency model* reflects the WFH frequency choice conditional on having access. Notwithstanding the selection process only having two dimensions compared to six of the frequency choice, more factors seem to explain this binary dimension. For example, both ISCO (job classification) and NOGA (industry classification) categories clearly explain whether or not an individual has the option to telework. On the other hand, once an individual has access, the two classifications no longer explain frequency variation (except for *construction* which intuitively would be expected to provide a strong signal). This suggests that understanding the detailed work task of an individual with home office access would be important. Broad classification seems not to be sufficient.

For the variables found to be significant for both model components, the signs align, meaning that if a variable increases the propensity to have access it also increases the propensity to telework more frequently. However, it is also interesting to realize that some effects are only significant for one of the components. For example, *Male* (gender) and *Higher education* only act via the selection component but do not affect the frequency.

Married couples living in the same household do much less telework than *divorced* or *married, separated* individuals. They potentially coordinate home office presence (trying to avoid being in the home office together with the partner).

Table 10: Estimation results: Heckman selection model

		Selection model		Frequency model	
	Coef.	Estimate	MPE [pp]	Estimate	Sens. [d]
Socio	Male	0.355**	5.609		
		(0.116)			
	Higher education	0.766***	12.737		
		(0.15)			
	Household income	0.032*	0.488	0.056***	0.082
		(0.013)		(0.01)	
	Divorced			0.347*	0.424
				(0.144)	
	Married, separated			0.64**	0.803
				(0.242)	
	Commute distance km (log)			0.099***	0.025
				(0.029)	
	Housing apartment	0.222*	3.517		
		(0.109)			
Work	Has manager role			−0.17*	−0.199
				(0.073)	
	Has company car			0.213*	0.256
				(0.102)	
	Firm size 10-49 employed			−0.324**	−0.37
				(0.104)	
	Firm size 50-249 employed			−0.284**	−0.327
				(0.093)	
	Firm size 250+ employed	0.352***	5.578		
		(0.105)			
	Fixed working hours model	−0.57***	−9.018		
		(0.124)			
	Works in shifts	−1.286***	−24.101	−0.914***	−0.92
		(0.216)		(0.212)	
ISCO	Clerical support worker	1.052***	15.894		
		(0.199)			

	Craft and related trades workers	−1.253***	−22.905		
		(0.26)			
	Elementary occupations	−0.91*	−15.868		
		(0.431)			
	Plant and machine operators and assemblers	−1.291*	−23.022		
		(0.573)			
	Managers	0.968***	14.733		
		(0.188)			
	Professionals	0.525**	8.193		
		(0.165)			
	Services and sales workers	−0.421**	−7.029		
		(0.162)			
	Technicians and associate professionals	0.486**	7.323		
		(0.174)			
NOGA	Accommodation and food service activities	−0.71*	−12.11		
		(0.36)			
	Construction	−0.774***	−13.102	−0.712*	−0.754
		(0.208)		(0.308)	
	Education	−0.94***	−15.929		
		(0.209)			
	Financial and insurance activities	1.21**	16.273		
		(0.449)			
	Human health and social work activities	−0.854***	−14.74		
		(0.177)			
	Information and communication	0.907**	12.782		
		(0.306)			
	Other service activities	−0.449*	−7.415		
		(0.198)			
	Wholesale and retail trade, repair	−0.716**	−12.158		
		(0.267)			
	Transportation and storage	−1.019***	−17.696		
		(0.26)			
Model	Sigma	0.669**		−0.41**	
		(0.244)		(0.151)	
	0|1			0.158	
				(0.386)	
	1|2			0.832*	
				(0.386)	
	2|3			1.451***	
				(0.389)	
	3|4			2.042***	
				(0.395)	
	4|5+			2.613***	
				(0.407)	
GOF indicators:					
N respondents		1914		1343	
N choice observations		1914		1343	
N parameters		30		47	
LL(null)		-1326.684		-2406.333	
LL(final)		-648.453		-2041.695	
McFadden R2		0.511		0.152	

Note: *5%, **1%, ***0.1%; standard errors in brackets

We now can compare the sensitivities of the frequency model with the sensitivities from the work arrangement model (Table 9). The work arrangement attributes generally have much smaller sensitivities (i.e., the effect is less substantial) as most of the factors presented in Table 10. For example, the previously elicited effect of partnership is much stronger than salary adjustments (which had the strongest effect among the proposed attributes).

4.4.2 MTO models

The MTO models are based on pooled RP-SP estimation where the *WFH frequency* sensitivity is exclusively inferred from the SP experiment.

The estimation results are presented in Table 11 and Table 12. Again, a claim to model the relation causally could be questioned by endogeneity issues: For example, *parking available at home* is almost certainly true if that individual owns a car (raising the issue of bias through reverse causality).

We first discuss the results in Table 11. The signs are plausible for all modes. For car and bicycle ownership many of the variables have information content, whereas the car sharing alternative is more difficult to model (i.e. there is no clear customer segmentation).

For car, the estimates are as expected and car owners are predominantly male, higher income, married, and living in rural or semi-urban environments. Parking availability plays a dominant role with large MPE. Only *secondary education* has a significant effect (which is also the case for GA ownership, as we will see). Having a company car also induces private car ownership. In contrast to the previous analysis, home office frequency no longer influences car ownership (the effect was already weak before), once we control for other factors. In fact, the home office treatment in the SP was not completely random (as the upper bound of the sampling interval was based on RP data, as explained in Section 3). Some of the included variables therefore seem to correlate with car ownership and this upper bound determining the home office potential.

Bicycle owners are predominantly male, Swiss, have short commutes, live in the city but do not necessarily work there (potentially as cycling is more convenient opposite the direction of rush-hour flows), and work part-time with a fixed working hours model. Living in an apartment building decreases the probability of owning a bicycle potentially

Table 11: Estimation results: mobility tool ownership (M)IV

		Car		Car sharing		Bicycle	
	Coef.	Estimate	MPE [pp]	Estimate	MPE [pp]	Estimate	MPE [pp]
Socio	Male	0.179^{*} (0.077)	3.867			0.132^{*} (0.063)	8.299
	Age			0.014^{**} (0.005)	0.984		
	Swiss					0.161^{*} (0.07)	10.242
	Secondary education	0.209^{*} (0.083)	4.566				
	Household income	0.034^{***} (0.01)	0.9				
	Married	0.28^{**} (0.089)	6.096				
	Commute distance km (log)					-0.079^{***} (0.02)	-1.056
	Parking available at home	1.434^{***} (0.192)	25.019				
	Parking available at work	0.617^{***} (0.078)	13.876				
	Housing apartment					-0.259^{***} (0.066)	-16.281
	Urbanization at home (low)	0.556^{***} (0.143)	12.53			-0.418^{***} (0.105)	-25.658
	Urbanization at home (medium)	0.568^{***} (0.084)	12.535			-0.208^{**} (0.065)	-13.115
	Urbanization at work (high)					-0.125^{*} (0.063)	-7.796
	Has driving permit					0.355^{***} (0.103)	22.049
Work	Has company car	0.402^{**} (0.132)	8.993				
	Works full-time					-0.274^{***} (0.07)	-17.531
	Annual working hours model			0.293^{*} (0.117)	4.502		
	Flexible working hours model					-0.161^{*} (0.081)	-10.297
	WFH frequency	-0.052 (0.041)	-0.156	-0.037 (0.048)	-0.16	0.01 (0.016)	-0.026
ISCO	Professionals			0.318^{*} (0.128)	4.879	0.15^{*} (0.068)	9.505
NOGA	Real estate activities	0.723^{*} (0.322)	16.347			-0.517^{*} (0.211)	-30.79
Model	No ownership|ownership (RP)	2.037^{***} (0.324)		2.732^{***} (0.384)		-0.278 (0.183)	
	No ownership|ownership (SP)	2.212^{***} (0.342)		1.773^{***} (0.321)		-0.296 (0.347)	
	Scale correction	0.687^{***} (0.071)		0.761^{**} (0.28)		1.859^{***} (0.2)	
GOF indicators:							
N respondents		1854		1854		1854	
N choice observations		3871		3871		3871	
N parameters		37		23		30	
LL(null)		-2683.173		-2683.173		-2683.173	
LL(final)		-1992.224		-935.141		-2412.903	
McFadden R2		0.258		0.651		0.101	

Note: *5%, **1%, ***0.1%; standard errors in brackets

because of limited high-quality parking availability.

We now shift to the PT modes (Table 12). Again, the signs follow intuition. Generally, the effects for GA and regional subscriptions are similar, suggesting a similar customer group.

GA users tend to not have children, have long commutes, no parking available at work, no driving permit, telework less frequently, and are occupied in service-oriented industries, public administration, or the transport industry. The influence of these NOGA sectors seems plausible since state-employed workers tend to have special GA offers as part of their fringe benefits.

A similar customer group can be identified for regional subscriptions. In addition, the subscription seems attractive for individuals working in rural areas and in small to medium-sized enterprises. Both subscriptions are substitutes for car as the customer segment and reversal of signs compared to car ownership suggests.

Half-fare card owners are high-income individuals, living in households with fewer adults, have no parking option at home or work, do not live in suburbs, work in urban areas in small to medium-sized enterprises, don't have a company car, and work part-time.

The different ISCO and NOGA sectors affecting the three PT subscriptions could be explained by different fringe benefit schemes or customer segmentation. For example, people in the transport sector are more likely to own a GA but less likely to own one of the other two subscriptions.

GA and regional subscriptions show rather small but significant WFH effects (the half-fare alternative no longer does). The WFH frequency was modeled as a continuous variable and MPE reflect a 10% increase. For example, if every person were to expand her WFH frequency by 10%, the GA ownership share would be reduced by 0.5%. These sensitivities align very closely with the average treatment effects discussed in Section 3.4: The model-implied sensitivities for GA and *Regional* are 3.1% and 4.7% respectively for the marginal home office day. The higher sensitivity of *Regional* seems intuitive, under the assumption that this subscription is in particular attractive for commuters working in closer vicinity to their homes.

The models presented in Section 4.4 are available as an API[13] with endpoints documenting the required variables as well as endpoints returning probability vectors/matrices for the respective model. Whereas regular estimated prediction functions could be easily rewritten in other languages (such as Python or Java) such is not the case for models with

[13] `https://github.com/dheimgartner/MATSimAPI`

Table 12: Estimation results: mobility tool ownership PT

		GA		Regional		Half-fare	
	Coef.	Estimate	MPE [pp]	Estimate	MPE [pp]	Estimate	MPE [pp]
Socio	Secondary education	-0.402^{***}	-9.469				
		(0.099)					
	Has children	-0.311^{**}	-7.368	-0.302^{***}	-7.059		
		(0.097)		(0.085)			
	Household income					0.025^{**}	0.878
						(0.008)	
	Number of adults living in household					-0.123^{**}	-0.719
						(0.043)	
	Commute distance km (log)	0.212^{***}	1.147	0.073^{**}	0.349		
		(0.043)		(0.028)			
	Parking available at home			-0.307^{*}	-7.207	-0.445^{**}	-12.356
				(0.148)		(0.139)	
	Parking available at work	-0.471^{***}	-11.249	-0.618^{***}	-14.653	-0.235^{***}	-6.92
		(0.101)		(0.084)		(0.07)	
	Housing apartment			0.369^{***}	8.664		
				(0.094)			
	Urbanization at home (medium)					-0.225^{**}	-6.583
						(0.075)	
	Urbanization at work (low)			-0.589^{**}	-13.332	-0.414^{**}	-12.331
				(0.223)		(0.149)	
	Has driving permit	-0.608^{***}	-15.544	-0.378^{**}	-8.865		
		(0.143)		(0.129)			
Work	Has company car					-0.218^{*}	-6.442
						(0.108)	
	Firm size 10-49 employed			-0.436^{***}	-10.032	0.263^{**}	7.475
				(0.116)		(0.081)	
	Works full-time					-0.223^{**}	-6.448
						(0.071)	
	WFH frequency	-0.117^{*}	-0.544	-0.191^{**}	-0.827	0.035	0.212
		(0.053)		(0.064)		(0.034)	
ISCO	Craft and related trades workers					-0.381^{*}	-11.309
						(0.16)	
	Elementary occupations					-0.645^{*}	-19.153
						(0.259)	
	Professionals					0.218^{**}	6.333
						(0.075)	
NOGA	Information and communication			-0.38^{**}	-8.745	0.27^{*}	7.685
				(0.142)		(0.118)	
	Manufacturing			-0.302^{*}	-6.963		
				(0.138)			
	Other service activities	0.384^{*}	9.585				
		(0.187)					
	Public administration and defense	0.474^{**}	11.909				
		(0.164)					
	Professional, scientific and technical activities			-0.401^{*}	-9.156		
				(0.189)			
	Transportation and storage	0.918^{***}	23.831	-0.451^{*}	-10.266	-0.383^{*}	-11.386
		(0.218)		(0.221)		(0.164)	
Model	No ownership|ownership (RP)	1.043^{***}		0.164		-0.521^{*}	
		(0.284)		(0.301)		(0.251)	
	No ownership|ownership (SP)	-0.632		-0.619^{**}		-0.61^{**}	
		(0.329)		(0.229)		(0.216)	
	Scale correction	0.734^{***}		0.636^{***}		0.79^{***}	
		(0.145)		(0.125)		(0.149)	
GOF indicators:							
N respondents		1854		1854		1854	
N choice observations		2885		2840		3871	
N parameters		35		34		30	
LL(null)		-1999.73		-1968.538		-2683.173	
LL(final)		-1139.348		-1435.795		-2459.451	
McFadden R2		0.43		0.271		0.083	

Note: *5%, **1%, ***0.1%; standard errors in brackets

Table 13: Out-of-sample validation (80-20 split)

Model	McFadden R2 (train)	McFadden R2 (test)	McFadden R2 diff.	Max diff. [pp]
Selection	0.511	0.498	0.013	0.442
Frequency	0.162	0.100	0.062	2.027
Car	0.246	0.290	0.044	0.757
GA	0.417	0.471	0.053	0.951
Regional	0.271	0.258	0.012	0.229
Half-fare	0.082	0.077	0.005	2.819
Car sharing	0.623	0.686	0.063	0.432
Bicycle	0.101	0.093	0.008	2.158

random components (since an algorithm is needed to identify the most likely position of each individual on the population distribution). The API is written in *R* and we therefore did not need to reimplement the prediction functions. The *plumber* package (Schloerke and Allen, 2022) was used to wrap these prediction functions.

4.4.3 Validation

Using the best-performing model specifications of Section 4.4 we retrained the model on a random sample of 80% and predicted on the hold-out sample. Further, we computed in-sample and out-of-sample *McFadden R2* statistics. A robust model should still outperform the Null model when applied to unseen data and it should do so in similar magnitude.

Table 13 presents these key indicators for all the models used in the MATSim simulation. The column *Max diff.* shows the biggest difference (in percentage points) comparing the observed shares to the true (out-of-sample) ones. The results strengthen our confidence that the models are suitable for predicting realistic shares in a simulation study. Additionally, the models should not only get the shares right, but they should also place certain individuals in the correct group with higher confidence (than for example the intercept-only model) and reflect the population segmentation as alluded in the discussion of the estimates.

5 Predicting the impacts of home-office on the transportation system

5.1 Introduction and motivation

The previous parts of the report have introduced models that predict the ability and willingness of an individual to work from home. Furthermore, they predict mobility tool ownership depending on the home office behavior. More specifically, given the characteristics of an individual, such as household structure, residence environment, workplace and job characteristics, the models return

1. the *ability* of this individual to work from home;
2. the (current) *frequency* of home office for this agent, i.e. the number of days per week when the individual is working from home;
3. the specific *days* of the week chosen as home office days;
4. the *mobility tools* the individual has access to.

Those models were estimated based on a survey conducted in the German-speaking Switzerland. Around 1000 respondents completed the parts of the survey that led to model estimations, as presented in Figure 1. Those findings need to be generalized to a full-size population, and translated in terms of travel behavior (different activities, different use of transport modes,...) in order to evaluate the impacts home office may have on the transport system.

The main objective of this chapter is to present the methodology used to:

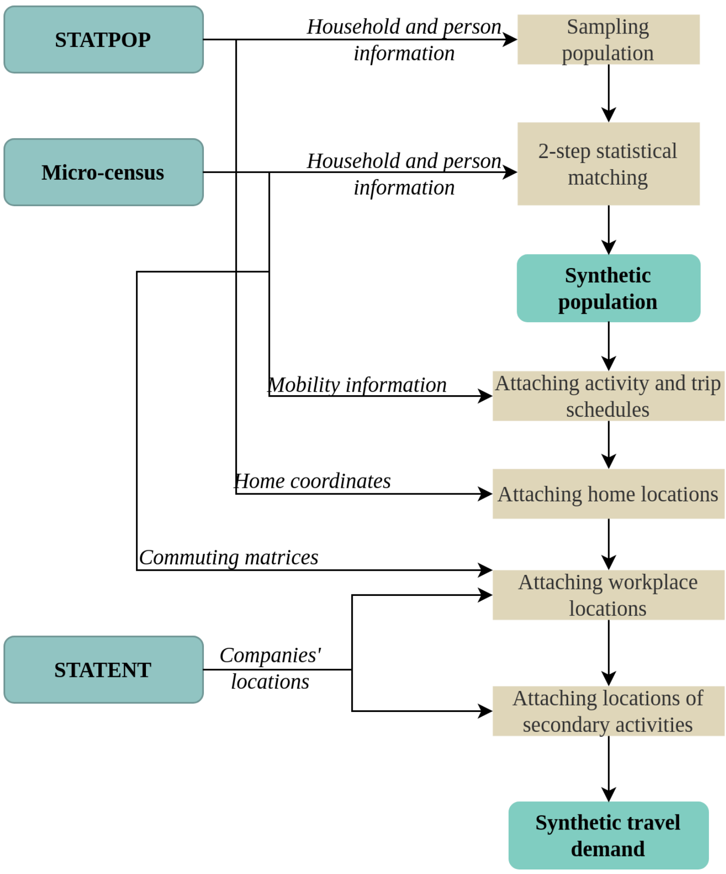
1. *generalize* the findings of this survey to a complete synthetic population of Switzerland;
2. *model* the (possible) impacts of home office on the population's travel behavior;
3. *run transport simulations* for Zurich corresponding to different working days and
   a) a population *before* home office is modeled in the synthetic population;
   b) a population *after* home office is modeled in the synthetic population;
4. *evaluate* the consequences that home office will induce on the transport system.

5.2 Generation of the synthetic travel demand

5.2.1 The eqasim pipeline

The *eqasim* pipeline(Hörl and Balać, 2021a,b) is used to generate the synthetic population (i.e. a set of synthetic agents representing all the residents of the study area) and the corresponding travel demand (i.e. information about the trips and activities the synthetic agents engage in). Starting from raw data, a sequence of stages are applied, which leads to outputs that can be used to run agent-based transport simulations. A detailed presentation of each stage and of the data sources can be found in Tchervenkov *et al.* (2022). The next paragraphs give a brief overview of the pipeline and of the datasets, which is summarized in Figure 22.

Figure 22: Overview of the eqasim pipeline.



5.2.2 Generating the synthetic population from the population census

The population census: STATPOP. Conducted as part of the federal population census, the population and household statistics data (Federal Statistical Office, 2012) of Switzerland (STATPOP) is a survey providing information about each resident of Switzerland at both household and individual level. For this project, the 2012 release was used. The dataset thus comprises information about all 7.997 million inhabitants living in Switzerland when the federal population census was conducted. Some of the relevant attributes include:

1. at the household level:
   - municipality identifier corresponding to the municipality the household lives in,
   - home location at the coordinate level,
   - household size,
   - a variable used to distinguish between "public" and "private" households, the latter referring to a person, or a group of persons, occupying the same residence and not having another living place.
2. at the individual level:
   - age and gender of the individual,
   - citizenship and residence permit information,
   - marital status.

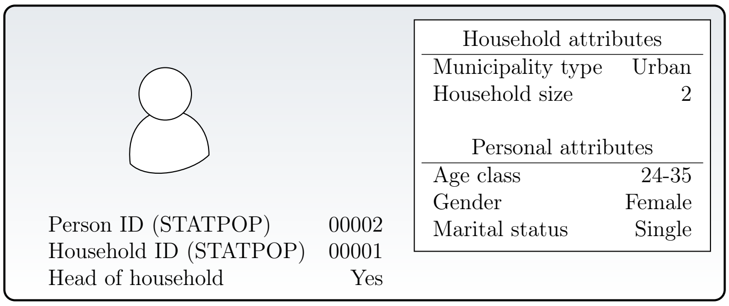
Generation of the synthetic population. The STATPOP dataset is used as a basis to build the synthetic population. After the raw dataset was processed and cleaned, one head of household is assigned to each household. This allows to impute other attributes at the household level in later stages of the generation process. The information known about the households' residence is enhanced with attributes describing, among others, the accessibility using public transport or the observed population density.

The resulting population dataset is then *scaled* using a multilevel IPF algorithm (Müller and Axhausen, 2011; Müller, 2017). This allows to not only generate a population for the exact year when the census data was collected (2012), but also to "project" this population onto "future" situations. In this study, we used tables published by the Federal Statistical Office (2021) providing counts of residents by canton, age, gender, and nationality (Swiss or non-Swiss) to weight the STATPOP data so that it represents the year 2020.

Ultimately, we are interested in *sampling* a subset of this full-size population to accelerate the later stages of the pipeline. Here, we used a sampling rate of 10%, meaning that 10% of the households comprised in the scaled population are selected based on the weights returned by the IPF algorithm.

The output of this first step is a dataset containing records about approximately 860 000 individuals, which correspond to 10% of all Swiss residents in 2020. This dataset is called the *synthetic population*. An example of a record from the synthetic population is provided in Figure 23.

Figure 23: Example of an individual from the synthetic population. Only a few personal and household attributes are represented.



5.2.3 Modeling the synthetic population's travel behavior using the national travel survey

The national travel survey: MZMV. The *Mikrozensus Mobilität und Verkehr* (Federal Office for Spatial Development and Federal Statistical Office, 2017) (mobility and transport microcensus) is the source of the mobility data used in this study. It is conducted every five years across Switzerland. Here, we are using the 2015 release. Around 0.5% of the Swiss resident population (57 090 persons, generally no more than one person per household being interviewed) provide insights into their personal and household living situation and into their mobility habits. Moreover, they have to report all trips they performed during one specific day. Each observation reported by the micro-census is weighted at the household, person and trip level. The dataset is processed and transformed into three data bases, containing respectively information about the households, the individuals and the trips. Among others, the attributes we are considering include:

- on the household level:

  - home location at the coordinate level,
  - household size,
  - number of bikes, cars and motorcycles owned by the household,
  - income class,
  - age and gender of each household member.
- on the person level:
  - age and gender of the individual,
  - marital status,
  - employment status,
  - highest education degree,
  - ownership of PT subscriptions,
  - driver's license ownership and car availability[14],
  - some attributes about the interview date, especially the day of the week, are reported too.
- on the trip level:
  - departure and arrival time,
  - activity conducted at the origin and at the destination, categorized into 6 activity types: home (H), work (W), education (E), shopping (S), leisure (L) and other (O).
  - location of the origin and destination at the coordinate level,
  - Euclidean and network distance between the origin and the destination,
  - main transport mode used for the trip, categorized into 5 modes: car, car passenger, public transportation (PT), bike and walk.

All micro-census respondents belong to different households and are more than 6 years of age. As our study is focusing on working days (Mondays to Fridays), the information related to individuals who reported their mobility behavior on a weekend day was removed from the dataset.

The statistical matching algorithm. The goal of this stage is to add mobility information to the synthetic population. To do so, we use the statistical matching algorithm, introduced by D'Orazio *et al.* (2006). Concretely, given a *source* dataset (here, the micro-census) and a *target* dataset (for our study, the synthetic population built from STATPOP), a record from the source dataset is attached to each record from the target dataset based on their

[14]The car availability defined at the individual level might be different from the attribute describing the number of cars owned by the household, for instance if the respondent has access to rented cars through their company.

similarity regarding specified attributes. This process is realized in three steps:

1. Additional household attributes are attached to the synthetic population. Those attributes include household income and car and bike ownership. In practice, each head of a household from the synthetic population is matched with a person record from the micro-census. The attributes of interest are their age class, gender, marital status, household size and residence environment. Once the matching is done at the level of head of households, the newly assigned attributes (household income, number of cars and number of bikes) are adjusted for all household members.
2. All attributes mentioned in the first step (age class, gender, marital status, household size, residence environment, household income, number of cars, number of bikes) are used to match a record from the micro-census dataset to each synthetic individual. The output of this step is an extended synthetic population containing information from STATPOP, matched household attributes regarding the income and mobility tool ownership and the identifier of a personal record from the micro-census. While the mobility tool ownership will be modified by the application of the econometrics models to the synthetic population (see subsection 5.3), this step ensures that the initial mobility tool ownership distribution in the synthetic population is consistent with micro-census observations.
3. Information about trips and activities from the micro-census are assigned to each synthetic individual according to the person identifier attached in the previous step. At this point, it must be noted that the locations are not included in the mobility information set. The reason is that the matching process shuffles activity chains around Switzerland, so that new locations must be sampled for each synthetic agent.

This process ensures that:

- The synthetic population contains consistent information regarding monthly income and mobility tool ownership at the household level, as these pieces of information were missing from the STATPOP dataset but are major factors influencing the individuals' mobility;
- Each synthetic individual is assigned mobility behavior data that correspond to their major characteristics. Here, we consider both individual characteristics, such as age or position within the household, and household characteristics (car and bike ownership, income).

At this point, the output of the pipeline is an extension of the synthetic population. The synthetic individuals now have:

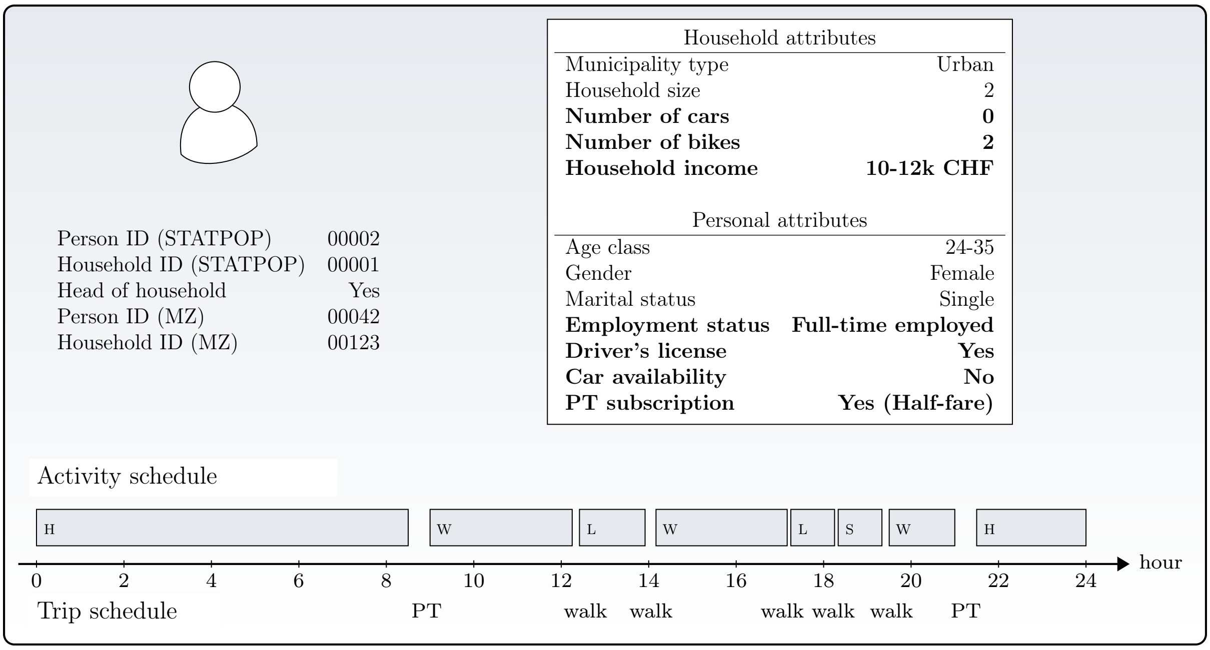
- more attributes. The synthetic population directly obtained from STATPOP is a set of records with a "minimal" set of attributes, including age, gender, marital status, household size, Swiss citizenship, and spatial information about the home location. After statistical matching, the synthetic individuals are characterized not only by those variables, but also by the household income, the number of cars and bikes owned by the household, and by other attributes obtained from the micro-census: ownership of a public transport subscription and of a driver's license, employment status, car availability.
- a *daily activity schedule*, comprising of information about all trips and activities the individual performed during the simulated day.

An example is depicted in Figure 24. The personal and household attributes written in bold – number of cars and bikes, household income, employment status, driver's license, car availability and public transport (PT) subscriptions – are those obtained from the micro-census (referred to as "MZ" below). According to the process described above, the activity schedule attached to this agent was copied from the micro-census respondent whose identifier was matched to her. While the chosen transport modes are optimized during the MATSim simulations (see subsection 5.5) and the trip durations might vary in the simulations due to congestion in the network, the initially imputed modes and trip schedules serve as references, both for the required location assignment step described above and for the plans run during the first simulation iteration.

5.2.4 Attaching information about visited locations from the national enterprise registry

The enterprise registry: STATENT. In the process of building the synthetic travel demand, the last step consists of attaching locations to the activities conducted by the synthetic individuals. The main data source is the STATENT dataset (Federal Statistical Office, 2015). This database is released yearly. In our study, we are using the 2014 release. The reported data is collected from the Federal Business and Enterprise Register (Federal Statistical Office, 2024a). The STATENT dataset provides information about all workplaces in Switzerland. Thus, not only information about private companies is collected, but we also have access to data about schools and public administrations, for instance. The locations of those workplaces are reported at the coordinate level. Moreover, for each record in the dataset, its corresponding economic sector(Federal Statistical Office,

Figure 24: Example of an individual from the synthetic travel demand and her activity schedule. H=home, W=work, L=leisure, S=shopping, PT=public transport.



2024b) (NOGA) and the number of full-time equivalent employees (as a total and by gender) are reported.

A sequential process to attach location information. As mentioned in the previous paragraph, 6 activity types are considered in the eqasim pipeline: home, education, work, shopping, leisure and other. Home, work and education are defined as *primary* activities and only one location can be attached to them. Consequently, if an agent is going twice to the office during the simulation day, the two corresponding activities will take place at the same location. Shopping, leisure and other are *secondary* activities and can take place at different places over the day. While the description of the detailed process used to assign locations to activities goes beyond the scope of this report, the core idea is summarized below:

1. *Home* locations are directly obtained from the synthetic population, as the STATPOP dataset contains information about the households' residences.
2. *Work* locations are selected from the STATENT dataset based on origin-destination matrices extracted from the micro-census.
3. For *education*, the corresponding places from STATENT are first categorized based on the age of the attending pupils or students: kindergarten for pre-school children, primary school for children aged 6 to 11, until universities and advanced professional

traning facilities for adults. For each agent participating in an education activity, the education place is chosen among the ones that are of the right type and closest to their home location.

4. The locations where *secondary* activities take place are sampled by a process described in detail in Hörl and Axhausen (2023).

The output of this stage is named the *synthetic travel demand*: each synthetic agent is associated with a full *mobility plan*, i.e. full information about the trips and activities they perform:

- for the trips, the origin and destination are known, as well as the transport mode used and departure and arrival time;
- for the activities, both start and end times are known, as well as the location where the activity takes place and the purpose of this activity.

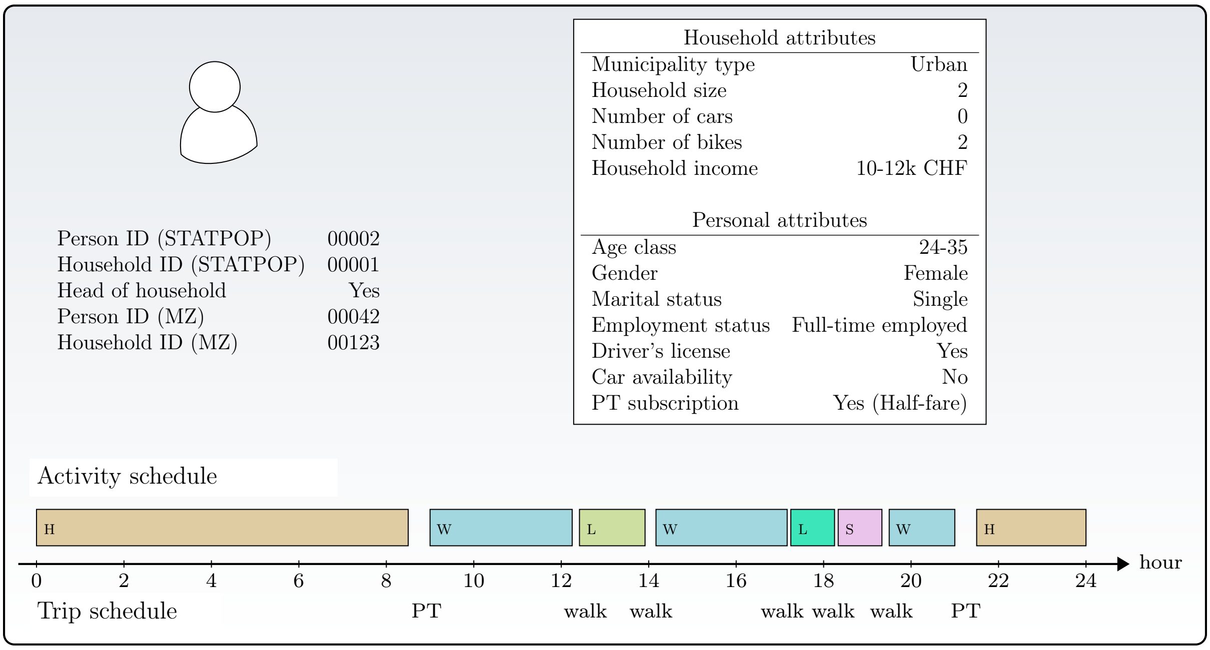
5.2.5 Overview of the synthetic travel demand

A record from the synthetic travel demand is depicted in Figure 25. Compared to Figure 24, all activities are now consistently connected with facilities, each of those facilities being represented by a different color.

5.3 Adaptation of the synthetic travel demand to the home office and mobility tool ownership models

The first challenge addressed was the integration of the models presented in section 4 into the travel demand generation pipeline. This involved adapting the sequence of stages to ensure that the synthetic population contains the necessary attributes for the models to be applied.

Figure 25: Example of an individual from the synthetic travel demand and her activity schedule. H=home, W=work, L=leisure, S=shopping, PT=public transport.



5.3.1 Modeling all necessary input variables

Table 10 and Table 11 present the variables required for the models. While some of them, such as `age`, Swiss citizenship (`swiss`), or driver's license ownership (`is_driver`), are already included in the synthetic population, others, such as gender (`sex_male`), and household income (`hh_income`), require appropriate re-categorization. Additionally, many attributes are absent from the synthetic population and need to be added or constructed using various data sources.

Household attributes. Insights from the micro-census, such as ownership of secondary residences and the presence of parking spaces at home, allow for the construction of appropriate variables (`re_2nd_ch`, `re_2nd_out`, and `parking_home`). `Urbanization` attributes are assigned to each household based on their home location, which is extracted from the STATPOP data. However, residence type (apartment or single house) is not described in either data source. To address this, and thus construct the corresponding model variables (`re_type_apartment` and `re_type_single_house`), we assign a residence type to each household based on the observed frequencies.

Attributes describing the household structure, such as number of adults (`n_adults`) and small children (`n_small_children`) in the household, were collected from the micro-census too. All those variables (secondary residences, parking space at home, number of adults and young children, residence type, urbanization level) were merged into the synthetic population at the household level, which means that all synthetic individuals belonging to the same household have the same variable attribute.

Personal and employment attributes. Expanding household variables to include individual characteristics like marital and parental status is required to run the models. While not directly available in existing datasets, this information can be indirectly learnt from individual attributes and household characteristics. For instance, the variable `has_children` is inferred from the individual's age, presence of children in the household, and reported household type. Marital status is derived by merging micro-census categories with household type information to obtain the new attributes `marital_status_divorced`, `marital_status_married`, and `marital_status_married_sep`.

Other individual attributes are related to the agents' educational background and current employment situation. The `education_secondary, mandatory` and `higher` variables and those describing the employment status – full time, multiple part time or part time job(s) – are extracted and re-categorized from micro-census records. Other variables, including `is_leader`, the `ISCO` description of the agents' jobs, their work schedule (`wk_schedule_fixed` and `wk_schedule_flexible`), and the `NOGA` sector which their company is attached to, are obtained from the micro-census. However, a large share of the employed micro-census respondents did not provide all necessary information while answering the corresponding questions. Moreover, some categories used in the micro-census do not overlap at all with those required for the models. For instance, while it is possible to detect the agents having a fixed or flexible work schedule, those working on an annual working hours model or working in shifts cannot be identified. In order to fill in the missing data, the following process was implemented:

- **Work schedule imputation:** as mentioned above, the agents having either a fixed or a flexible schedule are accurately identified. Those having different employment settings are assigned a work schedule, among "annual working hours", "shift work", or "other" based on the observed frequencies of each category reported by the survey respondents (see Table 2).
- **Access to a company car:** this information is not reported by any data source. Once again, we thus used the observed expectation of an individual having access to a company vehicle, computed from the survey results to draw individuals with this characteristic.

- **Number of employees in the employing company:** The micro-census does not provide information on company size, which is crucial for analyzing various workplace-related attributes. To address this, we computed the probability distribution that correlates company size with the NOGA sector, using the STATENT dataset. For employees with a known NOGA sector, a company size category is sampled from this probability distribution.
- **NOGA sector and company size:** some micro-census respondents did not provide information about the economical (NOGA) sector their company belongs to, which prevented us from transferring this information to the synthetic population. There are thus synthetic agents with a missing NOGA sector. We decided not to assign them a NOGA sector, as if they were working in a sector not covered by the `wk_noga` variables from the model, but we used a similar probability distribution as the one described above, only aggregated on all NOGA sectors, to determine the size of the company the agent works for.

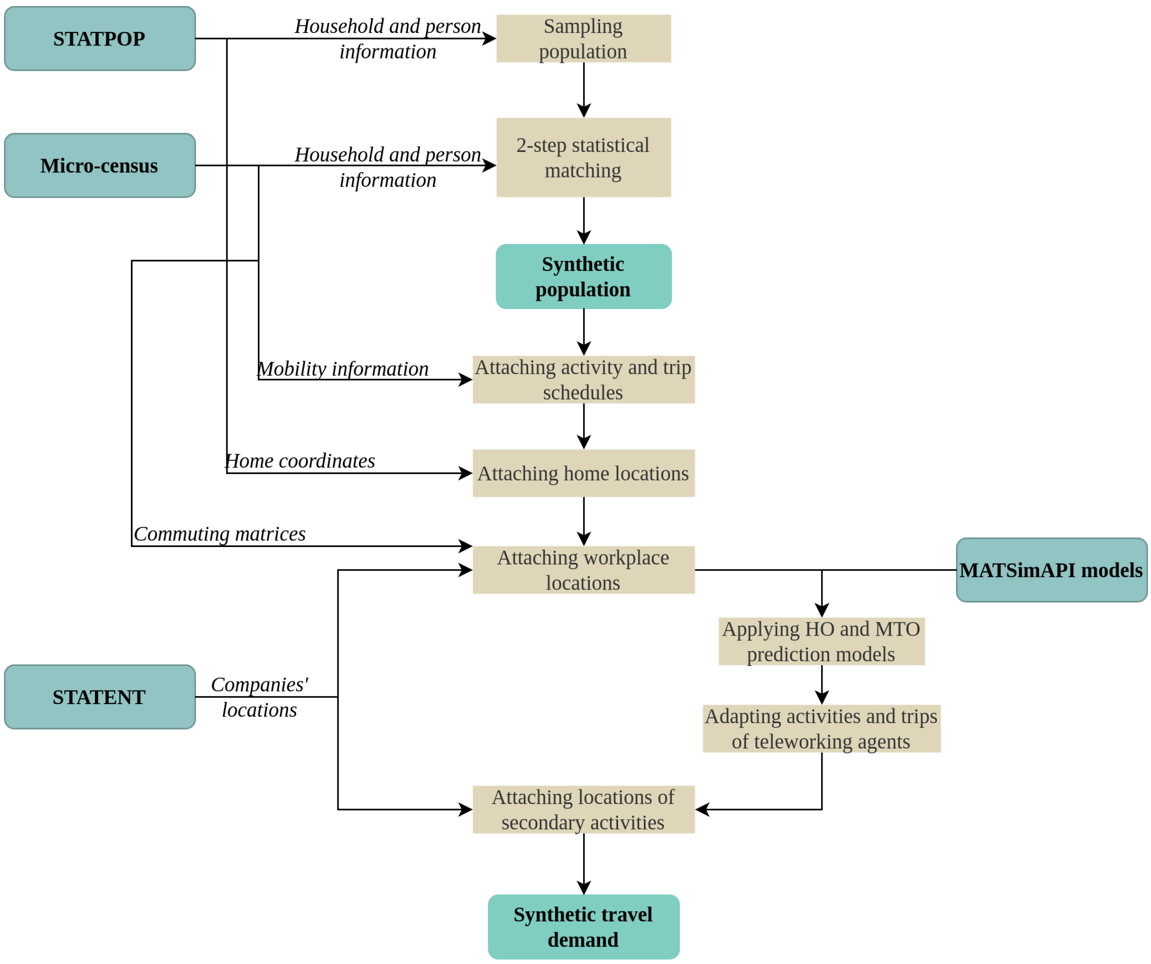
Workplace location attributes. The last required attributes – urbanization level at the workplace and log of the commute distance – concern the exact place where the agents work. Consequently, the synthetic population cannot be extended with the attributes described above before the agents' workplaces are known. Thus, the structure of the final pipeline is depicted in Figure 26.

5.3.2 Home office models

The models estimated in section 4 predict home office as a function of the set of attributes described above, and mobility-tool ownership as a function of the same set of attributes and home office. The first step is thus to predict the home office ability and frequency for every employed agent in the synthetic population, as well as the associated teleworked days of the week, before the mobility-tool ownership models can be applied.

A new stage was created and included in the pipeline; it is run once the synthetic population with extended attribute set has been created, as Figure 26 shows, and interacts with the MATSim API package so as to call the various models sequentially. In particular, the process is the following for the home office models:

Figure 26: Synthetic travel demand generation pipeline after modifications



1. Run the home office model.
2. The "selection" part of the model predicts, for each working agent in the synthetic population, the probability that this agent is currently able to work from home.
3. Sample, from the predicted probabilities, a binary variable (`wfh`) actually describing whether the agent is currently able to work from home.
4. Focus now on the "frequency" part of the model. The corresponding output is a vector describing the probability that the agents works from home on 0, 1,..., 5 days per week.
    a) For all agents who do not have the possibility to work from home (`wfh` = False), the frequency is set to 0.
    b) For all other agents, sample a frequency from the probability distribution given by the vector. This frequency (`wfh_frequency`) is an integer, ranging from 0 to 5, and denoting the number of days the agent is currently working from home.

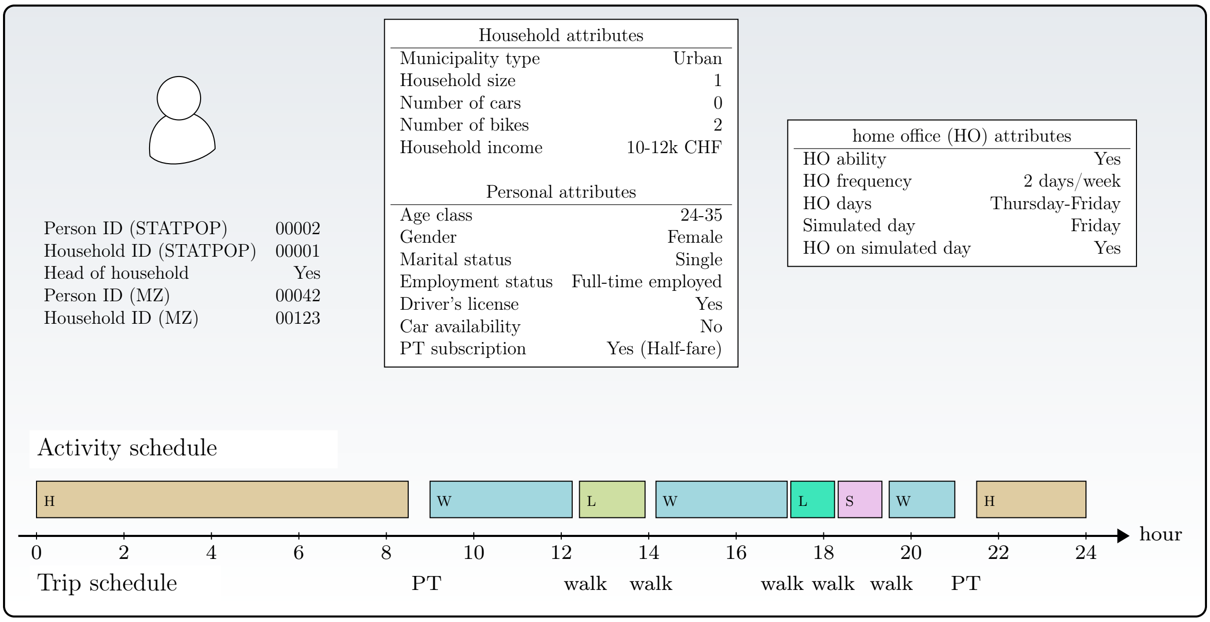
At this stage, the (extended) synthetic population dataset can already be used as an input to run the mobility-tool ownership models. However, we also need to predict the exact days when the agents work from home. The home office day assignment process uses another input of section 4: a table gathering the probability to work from home as a function of the predicted home office frequency and of the employment status (full time, multiple part time or part time) for each day of the week. This table is depicted in Figure 15 and is used to generate, for each employment status×home office frequency pair, the set of every possible home office day alternatives and their associated probabilities. Knowing their home office frequency and employment status, we can now sample the exact days when each agent prefers to work from home.

Day specific scenarios. This allows us to build scenarios representing specific days of the week, according to the following process:

1. Build the synthetic population, attach activity chains as presented in subsubsection 5.2.3, select workplace locations for all employed agents.
2. Expand the set of attributes in the synthetic population.
3. Run the home office models as explained above.
4. Attach one (working) day of the week to each agent according to the scenario specification. For instance, if the scenario aims to model an average between Tuesday and Wednesday, 50% of the population will be assigned to a Tuesday and 50% to a Wednesday.
5. Check whether the attached day of the week is part of the set of days (that can be empty) selected as home office days for each employed agent.
6. Those agents – that will thus actually work from home on the day the scenario aims to model – are identified; their activity and trip schedules will be adapted to home office as subsection 5.4 will present.

At this stage of the pipeline, the synthetic population is comprised of agents who can be represented as in Figure 27. For instance, given the socio-demographic profile of our example agent, she is likely to work from home on 2 days per week. The days predicted as home office days are Thursday and Friday, and as the current scenario aims to simulate a Friday, she is part of the agents who will work from home on the selected days and, consequently, whose plans need to be adapted.

Figure 27: Example of an individual from the synthetic travel demand and her activity schedule.



5.3.3 Mobility tool ownership models

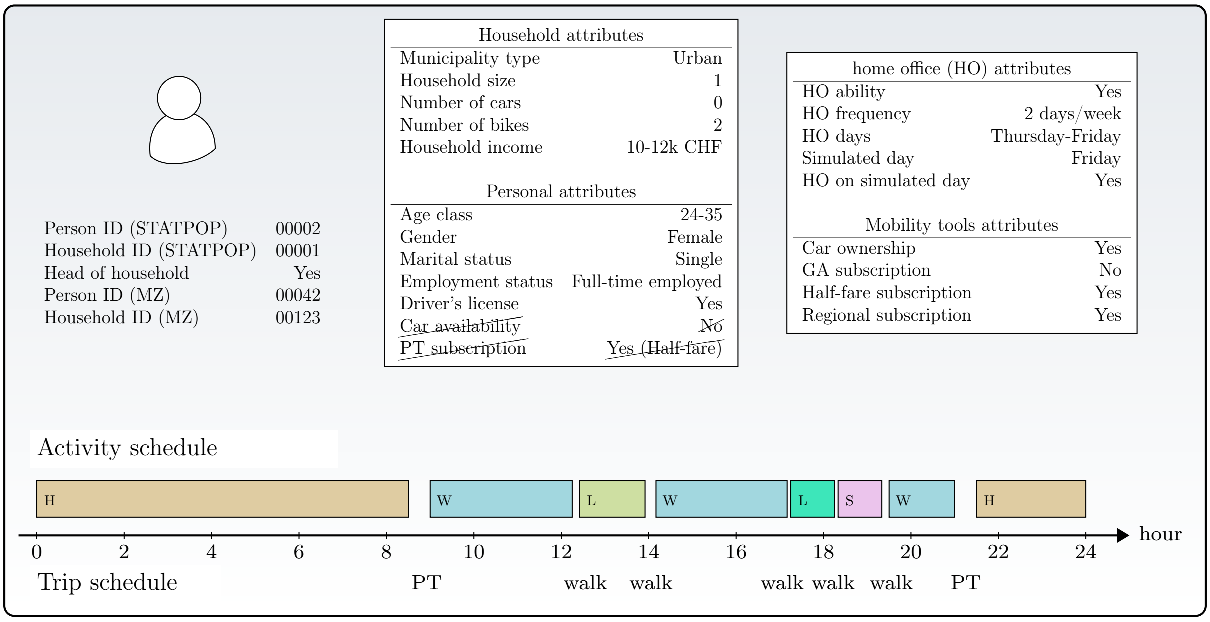
Once the agents able to work from home have been identified, the models predicting their mobility tool ownership can be applied. An observation here is that the models can only be applied to the employed population, as the home office attributes can only be predicted for working agents.

To ensure consistency between the working and the non-working parts of the population, we decided to scale the information provided by the micro-census about mobility tool ownership so that they match survey findings. The questions related to mobility tool ownership were asked differently in the micro-census and in the survey, which explains the extent of the observed difference, already reported in Table 6. For instance, while the micro-census reports that 85.1% of the individuals own a car, this share drops to 66.5% for the survey respondents. We thus selected 21% of the non-working agents owning a car and changed their attributes to remove any car access. As the models predict mobility tool ownership at the individual, and not at the household level, this modification is done only for the selected agents, not for their households.

For the working agents, who thus have known home office attributes, the mobility tool ownership is predicted thanks to the MATSim API. For both parts of the population, the mobility tool ownership is only adjusted for car and GA, half-fare and regional public transport subscriptions.

The impacts of applying the mobility tool ownership models on the synthetic population are depicted in Figure 28. The original attributes describing vehicle and public transport subscriptions ownership are replaced by those predicted by the models. For instance, while the agent had no access to cars, the models predicted that she actually owns a car.

Figure 28: Example of an individual from the synthetic travel demand and her activity schedule.



5.4 Four strategies to model home office

5.4.1 Motivation

The previous section described how discrete choice models were integrated into the synthetic travel demand generation process so as to identify the agents that work from home during the day of interest. This part of the report aims to describe the way their activity schedules change when the agents get the possibility to work from home. To adapt the plans, several questions need to be answered: do the working-from-home agents tend to cancel activities they would otherwise perform if they commute to the office? Do they choose different locations where they perform these activities? Do they travel significantly shorter distances than if they were commuting? Do these trends depend on the home office frequency? How do they evolve when home office becomes part of the "new normal" business life?

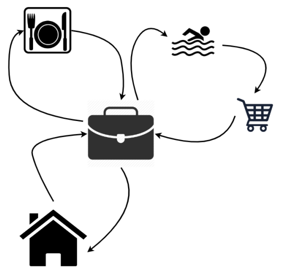
Detailed insights into the individual behavior of the agents is required to answer these questions. However, a large-scale dataset gathering information on trips and activities performed by working-from-home agents is not available:

- the 2015 release of the micro-census is a large-scale dataset. It was however conducted before home office has become usual in the general population. Hence, questions specifically targeting home office behavior of employed agents were not sufficient, and, most importantly, not related to the reported activities and trips performed on the interview date.
- the MOBIS-COVID survey (Molloy *et al.*, 2021b) was conducted between September 2019 and November 2022. 3700 respondents were invited to track their mobility over a period of 8 weeks using a GPS-based app. While the collected data is thus a great source of information on mobility during the various lockdown and mobility-restriction phases, only a very limited number of participants (less than 500) continued to track their mobility in the last months (Heimgartner and Axhausen, 2023). Moreover, potential biases in the responding population (the motorists are over-represented) make the generalization of findings from this survey uncertain.
- the 2021 release of the micro-census (Federal Office for Spatial Development and Federal Statistical Office, 2021) is based on data collected while the pandemic was affecting the observed mobility. Thus, even though the interviewed population covers, similar to the 2015 release, around 0.5% of the Swiss population, this data cannot be used for our study.
- the TimeUse+ data (Winkler *et al.*, 2022) was collected in late 2022, thus at a point where all pandemic-related mobility restrictions had been relaxed. Similar to the MOBIS-COVID survey, a GPS-tracking app was used to record activities and trips performed by the survey participants. The number of respondents is limited, as only 1318 of them completed all phases of the survey, and the observations are not weighted.

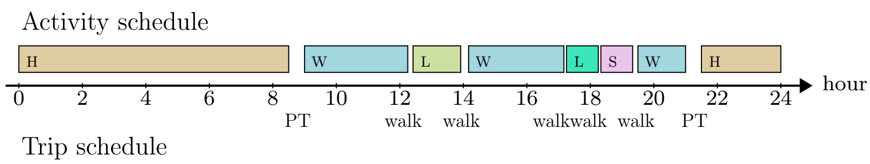
Consequently, no single survey can answer all of these questions. Our approach was thus to develop four strategies that would define how activity and trip plans are adapted as a response to the emergence of home office. One of them is based on the TimeUse+ survey and the other three are adaptations of the mobility data from the microcensus. Two dimensions were investigated: changes in the performed *activities* and changes in the activity *locations*. While many other dimensions, such as changes in the chosen transport modes, in the activity and/or trip durations, among others, could be analyzed, we will see in the next paragraphs that our approach is likely to cover a wide range of real-life situations.

The next paragraphs will introduce the four heuristics. The activity and trip schedule example already presented in Figure 24 and Figure 25 will be used to illustrate the impacts of each strategy on the agent's schedule. It is represented, both chronologically and spatially, in Figure 29. In this example, the agent leaves home at 8:30 and commutes to the office using public transport. At noon, she walks to a restaurant for lunch and goes back working shortly before 2PM. At 5PM, she trains at a swimming pool located close to her office, stops quickly at a supermarket to buy dinner and is back at the office for a late meeting at 7:30PM. Around 90 minutes later, she finally leaves the office and uses public transport (PT) to travel back home.

Figure 29: Example of an activity and trip schedule



a) Spatial representation of the activity schedule



b) Chronological representation of the activity schedule.
H: home, W: work, S: shopping, L: leisure; each color represents a different location.

5.4.2 Strategy 1: "staying home"

The first strategy aims to describe situations in which the agent cancels most of their activities and decides to spend most of their time home, either working or engaging in personal, or household-related activities. This can correspond to several real-life contexts:

- During lockdown periods, such as those implemented to contain the spread of the COVID-19 virus, numerous establishments offering "non-essential" services, including restaurants, indoor sports facilities, and non-food consumer goods stores, were closed. Moreover, working from home became mandatory or strongly recommended for employees with adaptable roles. This encouraged the general population to minimize outdoor activities and stay at home as much as possible.

- The evolving landscape of work arrangements has seen the introduction of flexible work models by many companies. This approach provides employees with the option to divide their time between remote work and office-based work, aligning with their preferences and job requirements. In this setup, employees can optimize their schedules by concentrating secondary activities, such as shopping, leisure, and social commitments, on office days. Conversely, they can focus exclusively on work and household responsibilities during remote work days, thereby alleviating the stress associated with commuting and thus improving their overall productivity.

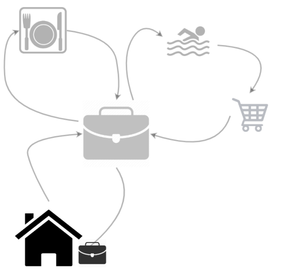
To model this schedule change, we have chosen to eliminate all "work" related activities. Specifically, we identify the tours (i.e., sequences of trips and activities starting and ending at home, without any intermediate home activity) that include at least one 'work' activity. All intermediate activities within these tours and the corresponding trips are removed from the plan. The activity locations are kept unchanged, except for the "work" activities which are replaced by (extended) work-from-home activities taking place at home. Algorithm 1 describes the process of adapting the daily schedules to the staying-home strategy.

Algorithm 1 Implementation of the staying-home strategy

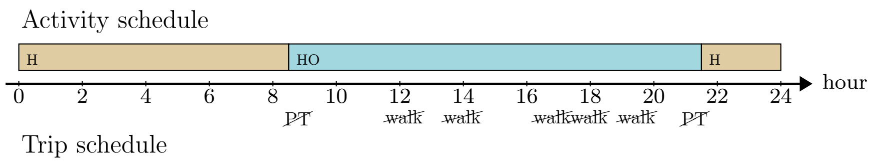
Require: a data frame describing the activities and the trips performed by the agent during the 24 hour period.
  Split the trips data frame into tours: $t_1, ..., t_n$.
  Identify the tours containing at least one work activity: $t_{i_1}, ..., t_{i_k}$.
  for $j \in \{i_1, ..., i_k\}$ **do**
    Identify the activities $\alpha_1, ..., \alpha_m$ and the trips $\tau_1, ...\tau_{m-1}$ corresponding to that tour.
    Replace the $m-2$ intermediate activities (i.e. not the home activities) by a single "home office" one, starting when α_1 ends and ending when α_m starts.
    Delete all $m-1$ trips.
  end for
  Assign to each "home office" activity the same location as home.
  Continue the generation of the synthetic travel demand with the assignment of facilities where secondary activities are performed.
  Build a new daily schedule from the modified tours.
  return the adapted activities and trip schedule.

For instance, the daily schedule from Figure 29 will be changed into the one presented in Figure 30. All secondary activities (lunch, sports training, stop at the supermarket) are part of a tour containing multiple "work" activities and they are thus cancelled. In this case, the agent spends consequently the entire day at home. The “home office” created by merging the work time with all cancelled activities is here obviously too long. However, from a travel demand modeling perspective, no distinction is made between all activities that take place home. Consequently, the extreme duration of the work-from-home activity has no impact on the simulation outcomes as we will focus on the trip-related aspects: the only important observation here is that there are no longer trips in this plan.

Figure 30: Activity and trip schedule adapted with the “staying-home” strategy



a) Spatial representation of the activity schedule



b) Chronological representation of the activity schedule.
H: home, W: work, S: shopping, L: leisure, HO: home office; each color represents a different location.

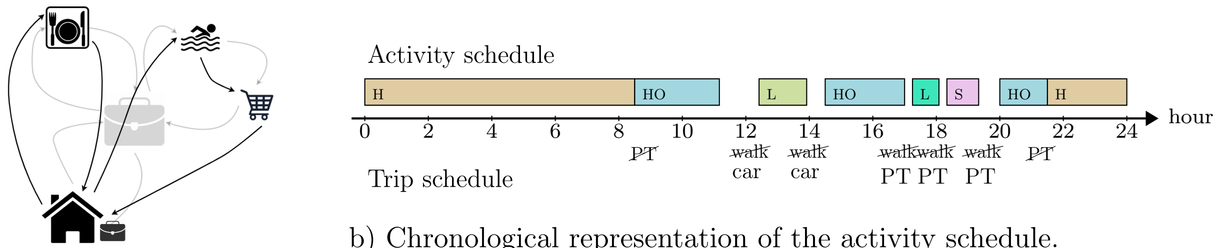
5.4.3 Strategy 2: "business as usual"

This strategy represents the easiest way an agent can adapt their schedule given that all their “work” activities are now replaced by “home office” ones. Contrary to the first proposed strategy, which induces the cancellation of the major part of the secondary activities, the activity schedule is kept unchanged, the only modification being that work activities are relocated to home for the teleworking agents.

A consequence is that some trips will last significantly longer than in the original plan, as Figure 31 shows. For instance, in the original schedule, the agent was going to a restaurant close to her office to have lunch. This restaurant will remain the same one in the final plan, but the place from which the agent is travelling to is no longer the office but her home. Similarly, for the end-of-afternoon activities, the starting point of the work-leisure-shopping sub-tour is no longer the (more convenient) office, but the agent’s home. Consequently, the agent might adapt the travel modes she chooses for each new tour.

This strategy might therefore seem unrealistic, but we think that it can still be applied, among others, by employees enjoying flexible work arrangements, for instance, if they have to join their colleagues in the office for a business lunch at their usual restaurant, or if their company subsidizes the subscription to a sports facility close to the headquarters. In those cases, the teleworking employee could be willing to travel longer to enjoy these social opportunities, without thinking of choosing more convenient locations to reduce their total travel time. Thus, this strategy could be chosen by workers whose job situation just became eligible to home office, as they didn't have the time to re-think their daily schedule.

Figure 31: Activity and trip schedule adapted with the second strategy



a) Spatial representation of the activity schedule

b) Chronological representation of the activity schedule. H: home, W: work, S: shopping, L: leisure, HO: home office; each color represents a different location.

An important observation here is that neither the departure and arrival times of the trips nor the chosen transport modes can be accurately computed again and adapted to the new workplace location by the synthetic travel demand generation pipeline. The entire optimization process resulting in a consistent schedule such as the one presented in Figure 31 takes place while running the MATSim scenario (refer to section 5), the input being a schedule with partly unrealistic schedules. For instance, in Figure 31, the mode (walk) and the corresponding travel duration (a few minutes) from the agent's place to the restaurant are copied from the original schedule, where the starting point was the office, which can be located several kilometers away from the agent's home. Algorithm 2 describes the implementation of this strategy.

Algorithm 2 Implementation of the do-not-change-the-locations strategy

Require: a data frame describing the activities and the trips performed by the agent during the 24 hour period.

Run the travel demand synthesis pipeline as if all agents were working in the office.

... including the secondary activity location assignment.

Once this is done, change the locations of all "work" activities to the agent's residence.

The trips are kept unchanged.

return the adapted activities and trip schedule.

Due to this technical challenge, and to the lack of time necessary to validate the implementation of this strategy, it was decided to exclude it from the scenario set that was considered in the context of this report.

5.4.4 Strategy 3: "adapting the locations"

The third strategy represents a situation in which the teleworking agents adjust the locations of the activities they perform to align with their new workplace location. In line with the second strategy, the nature of the activities performed by the agents remains unchanged. However, in contrast to the previous approach, the secondary activity locations are now tailored to the new workplace setting. This adjustment involves relocating these activities from their originally planned locations to accommodate the agents' remote work situation, factoring in the travel durations and modes outlined in the original schedule, as demonstrated by Algorithm 3.

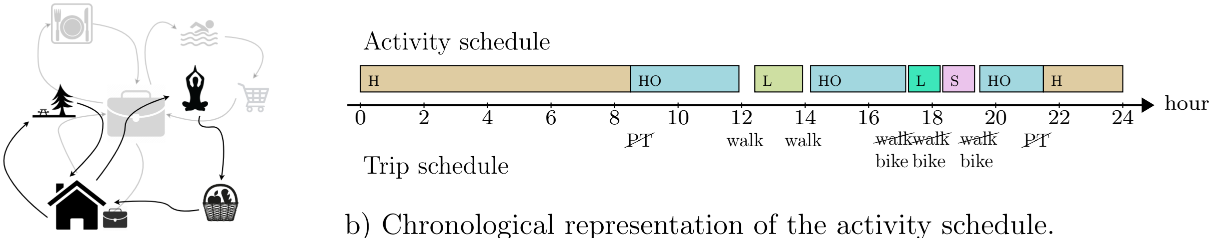
Algorithm 3 Implementation of the adapt-the-locations strategy

Require: a data frame describing the activities and the trips performed by the agent during the 24 hour period.
  Change the locations of all "work" activities to the agent's residence.
  The trips are kept unchanged.
  Run the last stages of the travel demand synthesis pipeline as usual
  return the adapted activities and trip schedule.

As the example depicted in Figure 32 shows, the new activity schedule looks more realistic than the one presented in Figure 31. Instead of the original business lunch, a picnic in a park was arranged. The sports training session was moved from a distant swimming pool to a nearby yoga studio, and the shopping activity was shifted to a local grocery market. Compared to the previous strategy, the travel times are kept short and the new activity locations might better represent the needs of the teleworking agent. As a result, this strategy may be suitable for agents who are accustomed to working from home but have not yet reevaluated the chaining of activities they perform.

A technical challenge emerged during the implementation of this strategy. Let's consider the example depicted in Figure 33. The agent initially relies on public transportation for their daily commute to the office, making a stop at a nearby supermarket on their way back. This supermarket conveniently sits near the office, likely along the same transit

Figure 32: Example of an activity and trip schedule

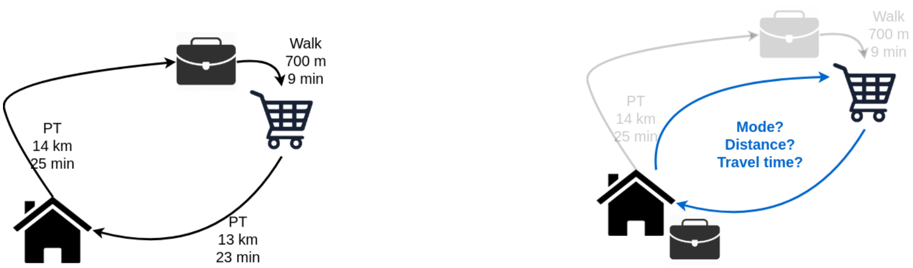


a) Spatial representation of the activity schedule

b) Chronological representation of the activity schedule.
H: home, W: work, HO: home office, S: shopping, L: leisure; each color represents a different location.

route the agent takes. Under strategy 3, traditional commuting is eliminated, yet the agent still needs to factor in time for shopping. The challenge lies in determining the optimal transport mode, trip duration, and travel distance for the "home-shopping-home" routine. Will the agent opt for public transit to reach the supermarket, or would they prefer walking? Are they inclined towards the nearest neighborhood market or are they willing to travel a greater distance? These questions cannot be definitively answered based solely on the initial schedule. One potential solution to this dilemma involves employing statistical matching at the tour level to estimate the missing trip details. For instance, by identifying a comparable "home-shopping-home" tour within the micro-census trips dataset conducted by an individual with similar characteristics to our agent, we can extrapolate insights regarding preferred transport mode, distance covered, and trip duration to inform the agent's revised schedule effectively.

Figure 33: Example of an activity and trip schedule, before while adjusting it to strategy 3 requirements



a) Initial trip schedule

b) Modifications of the trip schedule

5.4.5 Strategy 4: "TimeUse+"

With this strategy, contrary to the three other, the activity schedule that was attached to the agent from the micro-census is completely replaced with a new one.

The TimeUse+ study was conducted in the German-speaking Swiss regions from July 2022 to February 2023. The respondents provided personal and household-related information in two questionnaires and filled in an activity and trip diary based on a GPS tracking app. While the app automatically recorded start and end locations and times of events (trips or activities), the respondents annotated the passively collected data: they validated the events' durations and provided more insights into the performed activities. 63000 participants were invited and 1318 completed the three parts of the survey. For our study, we are only interested in daily activity chains that can correspond to home office days. The following cleaning process was thus applied to the data:

- Divide the tracking information into 24-hour data chunks and filter out days with untracked periods as well as week-end tracking data.
- Convert each 24-hour tracking data into activities and trips with a "usual" format. For the activities, the following information is extracted: activity purpose, start and end time. For the trips, the departure and arrival time, the travelled distance, and the chosen transport mode are obtained.
- Only extract the days corresponding to home office days. A complex heuristic was implemented here to select those days. For instance, if the respondent reported working from home only 30 minutes in the evening while they spent 9 hours at their office, this day is filtered out even though one home office activity was reported.

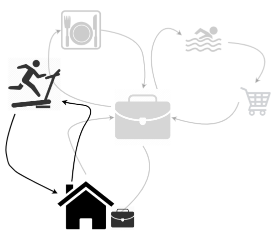
At this point, we are left with 2900 24-hour long activity and trip schedules belonging to 473 respondents that can be matched with agents selected to work from home. The statistical matching algorithm was used to match mobility data with the agents from the synthetic population. As the target agents are all adults and employed, the set of attributes used for the matching is different than the one used in subsubsection 5.2.3. Only 4 matching attributes are considered: age class, gender, car availability and marital status.

A significant challenge arises from the notable disparity between the mobility chains derived from tracking data and those reported in the micro-census. The micro-census, conducted via phone interviews, may lead respondents to omit certain short trips to streamline the reporting process. Furthermore, the time lapse between the trip occurrence and the interview may result in incomplete recollection. In contrast, the TimeUse+ data, reliant on GPS tracking, necessitates daily annotation and validation of activities and trips. Additionally, passive mobility data collection can artificially inflate trip numbers, such as detecting minor movements within a residence. While efforts were made to address these differences during TimeUse+ data preparation, the final dataset matched with teleworking agents may still exhibit differences compared to the micro-census.

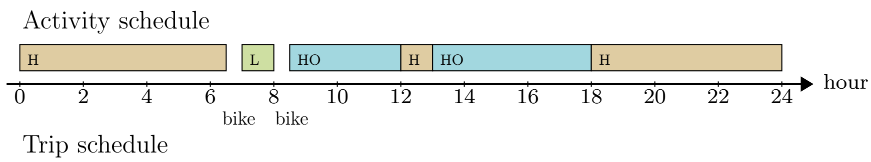
Despite the technical challenge, this approach offers numerous advantages. The survey, conducted in the latter half of 2022, occurred after the easing of all pandemic-related restrictions, with remote work having become a staple in the daily routines of many workers. Consequently, this strategy has the potential to simulate scenarios that extend beyond pandemic conditions, reflecting a reality where remote work is ingrained in the norm and telecommuters can genuinely tailor their daily schedules to their new work environments, distinguishing between the office and remote work days.

An example of a new daily plan obtained with this strategy is depicted in Figure 34. The agent's initial activity chain has been entirely replaced. She now commences her day with an early morning workout at a gym, returning home at 8:30 to begin her workday directly. Subsequently, she no longer leaves her home later in the day, alternating between home office periods and various domestic activities.

Figure 34: Example of an activity and trip schedule



a) Spatial representation of the activity schedule

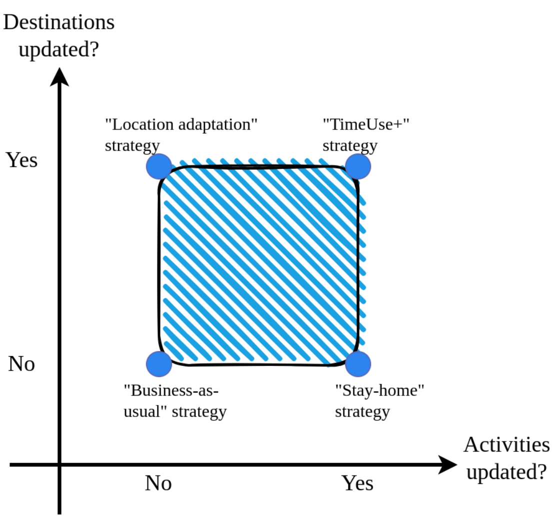


b) Chronological representation of the activity schedule.
H: home, W: work, HO: home office, S: shopping, L: leisure; each color represents a different location.

5.4.6 Summary

The last paragraphs described the four strategies that were implemented as possible ways to align the synthetic agents' mobility plans to their home office preferences. Two of them, namely strategy 1 (staying home) and strategy 4 (TimeUse+), imply that the initial activity plan is modified. Furthermore, two of them, strategy 3 (adapting the locations) and strategy 4 (TimeUse+), induce a modification in the locations that the agent visits. While many other dimensions are indirectly addressed by the different strategies, such as mode choice and trip duration, the development of those strategies focused on the impacts of home office on the performed activities and the visited locations. Thus, Figure 35 can represent the differences between the strategies. An important observation here is that we have no guarantee that one strategy can represent the way all teleworking agents adapt their plans to their home office preferences. Actually, as we highlighted while presenting the strategies, they all can represent various real-life situations. Consequently, the reality of a "normal" work day is likely not to be located at an edge of the square depicted in Figure 35, but it is rather situated within the square, and might depend on the day of the week, on each individual company's settings regarding home office and on the agents themselves. Thus, the scenarios that were built can only be interpreted as "edge cases". In particular, while the first strategy is likely to over-reduce the number of performed trips, the fourth one might instead under-represent the impacts of home office on mobility because of the bias towards longer activity chains in the dataset.

Figure 35: Overview of the different strategies



5.5 Scenario definition and calibration

5.5.1 From synthetic travel demand to MATSim scenarios.

MATSim, short for Multi-Agent Transport Simulation(Horni *et al.*, 2016), is a powerful tool used to simulate and analyze transportation systems. It operates by modeling individual agents, such as people or vehicles, making travel decisions based on their preferences and the available options. These agents interact with each other and the infrastructure, creating a dynamic representation of real-world transportation scenarios. In subsection 5.2, the eqasim pipeline was introduced as a method for generating the synthetic travel demand required to run MATSim scenarios. The transport supply is modelled by other stages in the eqasim pipeline. Their description goes beyond the scope of this study and can be found in Hörl and Balać (2021a,b).

Subsequently, subsection 5.3 and subsection 5.4 detailed the modifications made to this pipeline in the context of this study. Firstly, it outlined the prediction of agents' preferences regarding home office and the adjustment of their access to various mobility options. Secondly, it discussed the customization of mobility schedules for telecommuting agents according to four different strategies.

In this study, MATSim will be used to evaluate the impacts of home office on the transportation system. Various scenarios will be simulated. Each of them is implementing one of the four strategies presented in subsection 5.4 during one working day, or an average of several working days. Table 14 gives an overview of the simulated scenarios. First, a baseline scenario was simulated. The impacts of home office were not considered in this scenario but their access to various transport modes was updated; all agents thus commute to the office as reported by the micro-census, only the transport mode they choose might be impacted. This scenario serves as a reference to evaluate the effects of home office. Then, the strategies 1 and 4 were simulated, both first on an average Friday and then for an average between Tuesday, Wednesday and Thursday. In the Friday scenarios, all agents working from home on a Friday were assigned new mobility plans according to the chosen strategy. For the scenarios covering multiple days, we picked one target day for each agent. In our case, $\frac{1}{3}$ of the agents was assigned to each day between Tuesday, Wednesday and Thursday, and we adapted the mobility plans of the agents predicted to work from home on their assigned day.

Table 14: Overview of the simulated scenarios

<table>
<tr><th></th><th>Monday</th><th>Tuesday</th><th>Wednesday</th><th>Thursday</th><th>Friday</th></tr>
<tr><td>Baseline</td><td colspan="5">✓</td></tr>
<tr><td>Strategy 1</td><td></td><td colspan="3">✓</td><td>✓</td></tr>
<tr><td>Strategy 2</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Strategy 3</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Strategy 4</td><td></td><td colspan="3">✓</td><td>✓</td></tr>
</table>

5.5.2 Scenario definition and study area

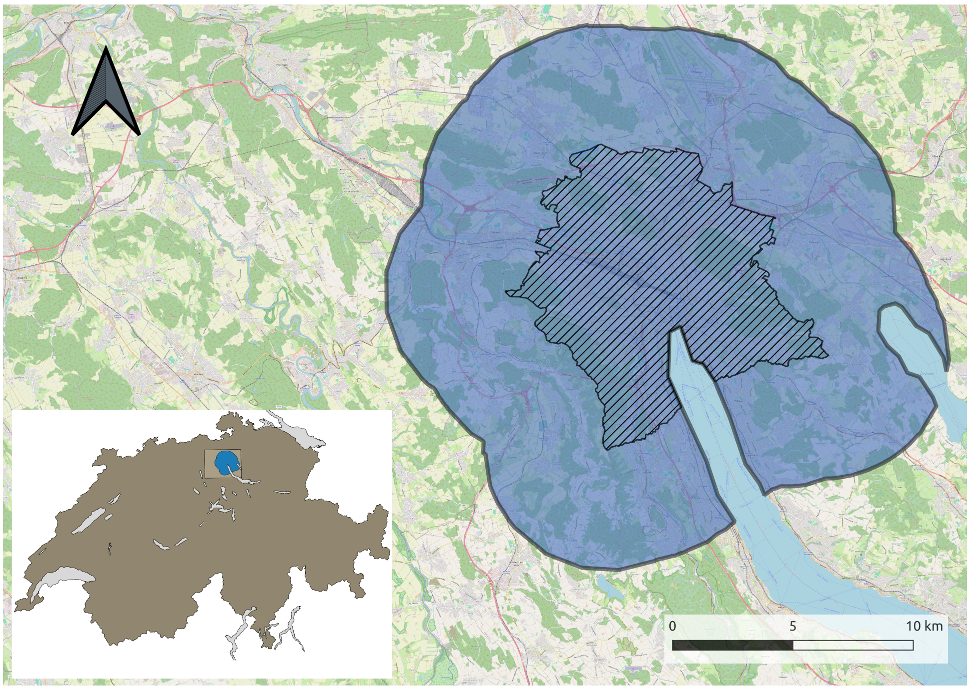
In this study, a sample size of 10% was used. The same population was used for all simulated scenarios, to ensure that no difference in the final results was due to the sampling process. We used the MATSim version 13.0 and the eqasim version 1.3.1.

To evaluate the impacts of home office on the transportation system, we decided to consider only the city of Zurich. Focusing on urban areas is crucial when evaluating the impacts of home office on the transportation system due to several key reasons. First, urban areas typically have higher population densities, leading to more significant transportation challenges and congestion. Second, due to the diverse range of transportation modes available, including public transit, cycling, and walking, we will be able to understand how home office affects mode choice and travel behavior in urban settings. Urban areas often face environmental issues such as air pollution and greenhouse gas emissions from transportation. Evaluating the impacts of home office on urban transportation can help assess the potential environmental benefits, such as reduced emissions and improved air quality, induced by the potential reduction of travel time and shift towards more sustainable transport modes. A final reason is that urban areas are hubs of policy innovation and implementation. By focusing on cities, policymakers can develop targeted strategies to optimize transportation systems in response to the growing trend of remote work facilitated by home office arrangements.

The study area is depicted in Figure 36. It consists of the city of Zurich, hashed in black in the figure, and of a buffer ranging up to 5km beyond the city borders. Not only the agents living in the study area are considered in the final population, which includes all agents performing at least one activity in the study area. Hence, an agent residing in Bern and commuting to Zurich, for instance, will be included in the scenario population. To generate this population, a three-step process is applied:

- first, the 10% synthetic population representative for Switzerland is generated and the MATSim scenario is run for 60 iterations;
- then, the scenario is cut around the study area, which means that only the agents performing at least one activity in the study area are selected to be part of the new population;
- finally, another MATSim scenario corresponding to this new population is run, once again for 60 iterations.

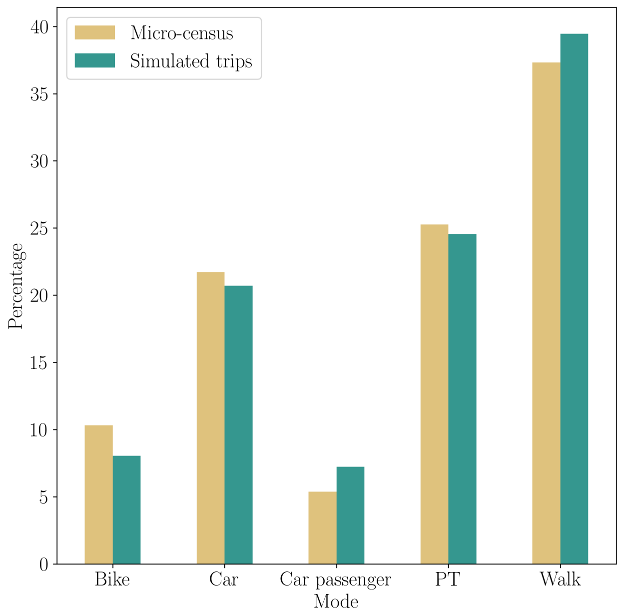
Figure 36: Scenario extent



The final population comprises of 127541 individuals in the baseline scenario. The number of agents in the population decreases in the home office scenarios. For instance, if we run the strategy 1 on an average Friday, the population only comprises 117787 individuals. The main reason explaining this reduction in the population size is the scenario cutting process, as it excludes all telecommuting agents living outside the study area and working in Zurich. If their trips to and from the study area were cancelled due to the application of the strategies.

The mode choice model used in the simulations is obtained from Hörl *et al.* (2019). A comparison of the mode share in the baseline simulated scenario and the micro-census is given in Figure 37. Only the trips conducted within the study area are considered. The figure suggests that, despite the changes in mobility tool ownership and thus in the access to various transport modes, the mode choice model is still appropriate to our scenarios.

Figure 37: Mode share comparison between micro-census and the baseline scenario (PT = public transport).



5.6 MATSim scenario results

This section presents the results of the simulations described in subsection 5.5. While the first two paragraphs validate the application of the models predicting home office and mobility tool ownership to the synthetic population, the major part of the section is devoted to the evaluation of the impacts of home office on the transportation system, considering various indicators, from mode share to detailed insights into the spatial and temporal analysis of the trips.

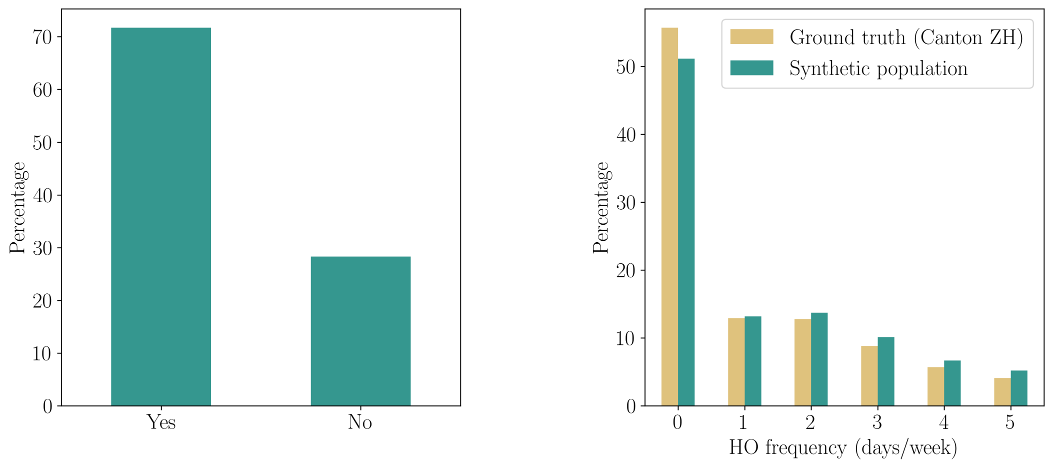
5.6.1 Home office in the synthetic population - validation

We first have to ensure that the models predicting home office ability, current frequency and days are appropriately applied to the synthetic population. Figure 38a shows that

71% of the employed agents from the synthetic population are working in teleworkable jobs. This observation seems reasonable considering that the study area, where the main part of the synthetic agents live, consists of dense urban areas. In the city of Zurich, 90% of the employed population is working in the service sector[15], 30% more specifically in the business services and the banking and insurance industries[16]. A share of 71% of agents working teleworkable jobs is thus likely.

Figure 38b compares the current home office frequency in the synthetic population and among survey respondents living in the canton of Zurich. The share of agents currently not working from home in the synthetic population (51.3%) seems to be under-represented compared to the survey population (55.7%). However, the survey population also comprises agents living in rural parts of the canton, away from urban centers, as it was not possible to identify more accurately the respondents' residence place. The synthetic population is consequently more urban, as the study area only comprises the city of Zurich and the neighboring urban area within a radius of 5 km. We can thus assume that the share of agents currently working from home is slightly higher in the synthetic population than among survey respondents, which is what Figure 38b depicts.

Figure 38: Agents working teleworkable jobs and current frequency of home office in the synthetic population. Unemployed agents are filtered out.



a) Ability to work from home

b) home office (HO) frequency

The share of employed agents working from home on each day of the week is depicted in

[15]`https://www.stadt-zuerich.ch/portal/en/index/portraet_der_stadt_zuerich/wirtschaftsraum_u_-foerderung.html`

[16]`https://eures.europa.eu/living-and-working/labour-market-information/labour-market-information-switzerland_en`

Figure 39. One can see that, as already described by Figure 15, Friday and then Monday are the two most chosen home office days, with respectively 31% and 25% of the employed synthetic agents. Tuesday, Wednesday, and Thursday are less considered as home office day options with, on average, 21% of the employed population telecommuting. Once again, the share of agents working from home is higher than what the original survey reported. The reason for this is similar to the one presented above: the survey population comprises here all survey respondents, who were sampled among residents of German-speaking Switzerland, not only among residents of the Zurich metropolitan area.

Figure 39: Share of employed agents working from home on each day of the week and comparison with survey respondents.

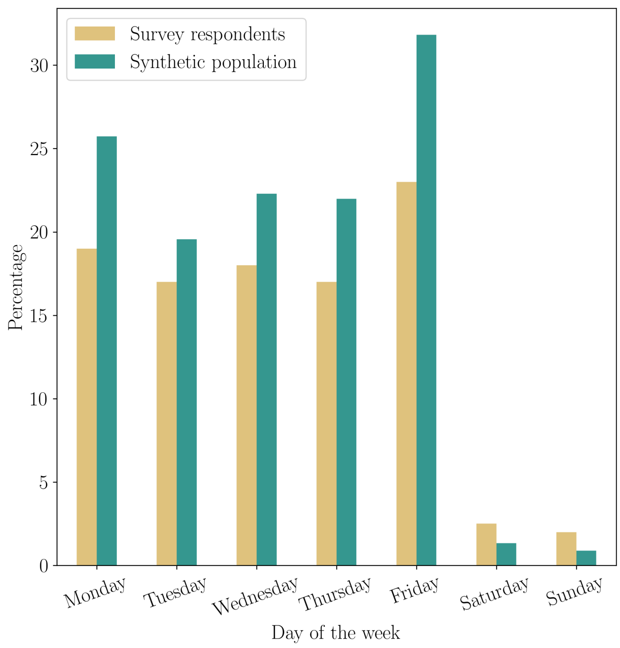
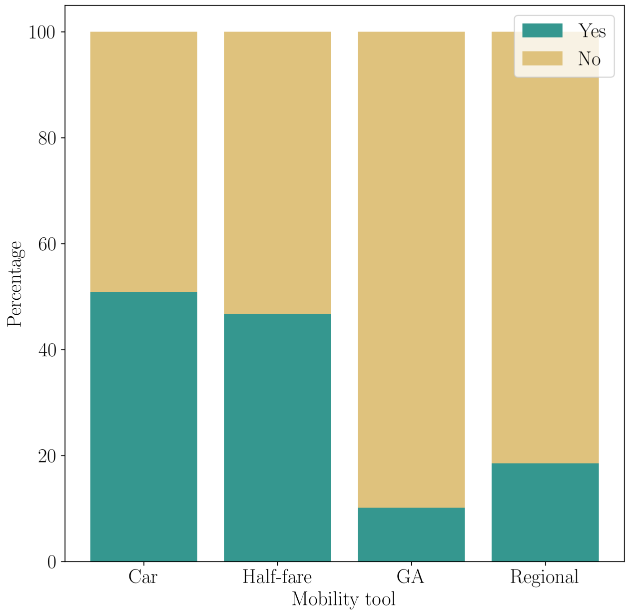


Figure 40 shows the mobility tool ownership in the synthetic population. While the micro-census reports that 60% of the population residing in Zurich has access to a car, this percentage drops to 50.9% in the synthetic population. A possible explanation for this gap is the way the car availability-related questions were asked in the micro-census questionnaires. Those questions indeed focused on the *access* to a car, not solely to the ownership of a private vehicle. The City of Zurich reports[17], using values from the 2021 release of the micro-census, that 53% of the households living within the city borders have no access to a car, which is close to the percentage found in the synthetic population (49.1% of the individuals have no access to a car).

[17] `https://www.stadt-zuerich.ch/site/umweltbericht/de/index/treiber/mobilitaet.html`

Figure 40: Mobility tool ownership in the synthetic population



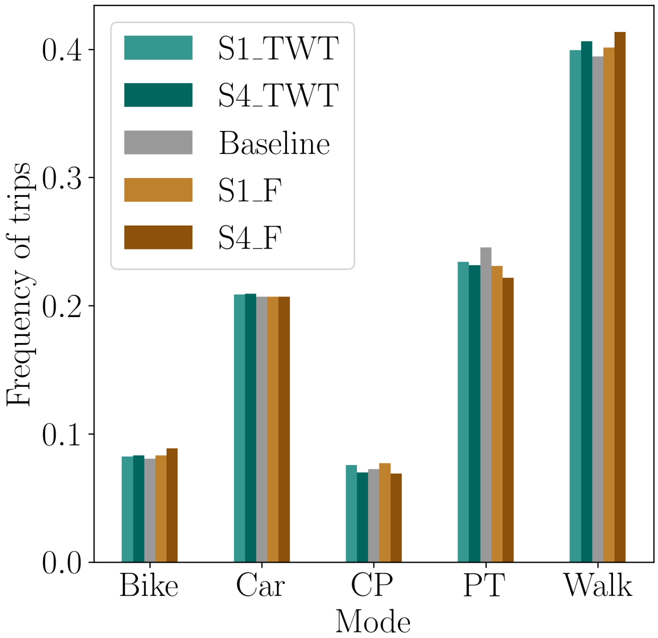
5.6.2 Mode share, number of trips, travelled distance and trip duration

The next paragraphs will report on the impacts of the home office emergence on various indicators, comparing the reference MATSim run with the four simulated scenarios (Table 14). The first indicator we propose to investigate is the mode share. The results of the comparison are depicted in Figure 41.

Among all scenarios, the mode share seems to remain very stable, with, for instance, 20% of all trips being done as a car driver for all scenarios. Only an almost negligible increase in the share of walk trips at the expense of transit ones can be observed in the Friday scenarios, compared to the baseline. This trend remains unchanged if we weight each trip by the travelled distance or the travel time.

While the mode share remains stable across all scenarios, a different observation can be made while looking at the evolution in the number of trips, travelled distance, and total trip duration. Those indicators are shown in Figure 42. The original 5 modes were categorized into three modes: motorized individual vehicle (MIV), gathering car and car

Figure 41: Mode share comparison - baseline vs. mid-week vs. Friday scenarios. S1 = strategy 1, S4 = strategy 4, TWT = Tuesday-Wednesday-Thursday scenario, F = Friday scenario, PT = public transport, CP = car passenger.

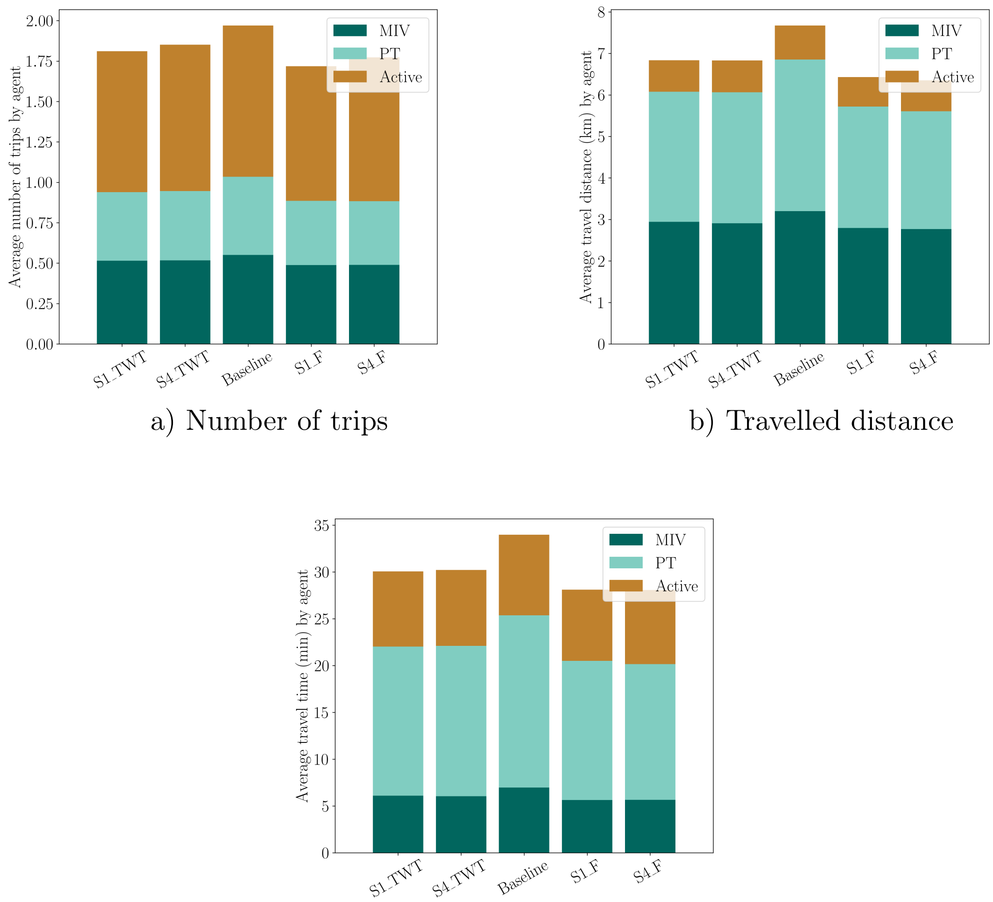


passenger; "active", which represents walk and bike trips, and public transit (PT).

For all home office scenarios, we can observe a decrease in the number of performed trips, as depicted in Figure 42a. While an agent performs on average 1.97 trips on an average working day in the reference scenario, this number drops to 1.81 (-8.1%) and 1.85 (-6.1%) in the mid-of-the-week scenarios with strategy 1 and 4 respectively and to 1.71 (-12.8%) and 1.77 (-10.0%) in the Friday scenarios. The most affected mode is public transit, with a number of trips reduced on average by 11.8% from Tuesday to Thursday and 18.4% on Fridays. The different strategies seem almost not to impact the results. The only observable difference concerns active trips: for instance, their number decreases by 11.0% in the Friday scenario with strategy 1, but only by 4.8% for the same scenario but with strategy 4. Possible reasons could be that the TimeUse+ data, used to implement strategy 4, over-represents short trips compared to micro-census findings, as explained in subsection 5.4.

Figure 42b and Figure 42c respectively show the impact of this reduction of the number of trips on the total travelled distance and the total trip duration. The relative differences

Figure 42: Number of trips, total travelled distance (in meters) and total trip duration (in seconds) between the scenarios.
S1 = strategy 1, S4 = strategy 4, TWT = Tuesday-Wednesday-Thursday scenario, F = Friday scenario, PT = public transport, MIV = motorized individual vehicle, Active = walk and bike.



a) Number of trips

b) Travelled distance

c) Total trip duration

in the number of trips, travelled distances, and trip durations are summarized in Table 15. In absolute values, both the travel distance and the trip duration are reduced by a larger intensity than the number of trips, indicating that the commuting trips, i.e. the ones majorly affected by the teleworking emergence, are longer in distance and duration than the other ones. For instance, in the mid-of-the-week scenario implementing Strategy 1, a reduction of 8.1% in the number of trips translates to a reduction of the travelled distance of 10.9% and to a reduction of the trip duration by 11.5%. The values are similar for the strategy 4. For Friday scenarios, it seems that the emergence of home office could help reduce the travelled distance by 16 to 17% and the travel time by around 17.4%, according to the implemented strategies.

Table 15: Evolution of the number of trips, travelled distance and trip duration in the different scenarios, compared to the reference scenario, in percentage points.

		Number of trips	Travel distance	Trip duration
S1-TWT	MIV	-6.5	-8.0	-12.7
	Active	-6.8	-7.2	-6.6
	PT	-12.4	-14.2	-13.4
	Total	-8.1	-10.9	-11.5
S4-TWT	MIV	-6.2	-9.2	-13.4
	Active	-3.2	-6.4	-5.8
	PT	-11.3	-13.6	-12.7
	Total	-6.0	-11.0	-11.1
S1-F	MIV	-11.3	-12.7	-19.2
	Active	-11.0	-12.7	-11.6
	PT	-17.9	-20.0	-19.2
	Total	-12.8	-16.2	-17.3
S4-F	MIV	-11.1	-13.4	-19.0
	Active	-4.8	-8.8	-8.2
	PT	-18.7	-22.4	-21.0
	Total	-10.0	-17.2	-17.4

Looking at the MIV values in Table 15 leads to an important observation: the reduction in trip duration is always much greater, in absolute value, than the reduction in travelled distance. For instance, in the scenario implementing the TimeUse+ strategy on an average Friday, a reduction of 11.1% in the number of trips and of 13.4% in the travelled distance corresponds to a reduction of 19.0% in the total travel time. This suggests that the average car speed increases with the emergence of home office. The following paragraphs will elaborate on this observation.

5.6.3 Number of trips, travel distance and trip duration, for commute trips.

Table 16 provides insights into the same indicators as Table 15, focusing on commute trips. We define those trips as trips starting or ending with a “work” activity. In all four non-baseline scenarios, one can see the decision of a portion of agents to telecommute directly corresponds to a proportional decrease in the number of commute trips, showcasing a consistent relationship between the two factors. For instance, 21% of the employed agents are working from home on an average day representing Tuesdays, Wednesdays, and Thursdays. For those days, the decrease in the number of performed trips has the same magnitude, reaching 19.7% with strategy 1 and -20% with strategy 4. Similarly, 31% of the eligible agents in the synthetic population are selected as working from home on Fridays and the number of commute trips is reduced by 31% and 32.3% respectively with strategy 1 and 4. All modes (MIV, PT and active modes) are similarly affected, contrary to what Table 15 showed.

As the number of trips to and from workplaces decreases, the reduction in traveled distance and travel duration using transit and active modes mirrors this decline proportionally. Moreover, similar to what we observed before, we can notice that the decrease in travel time by car is more substantial than the corresponding decrease in traveled distance. For instance, with strategy 1, on Friday, the travel distance drops by 29.8%, corresponding to a decline of 37.6% in travel time. Once again, this suggests that home office contributes to achieving less congestion and higher speed levels for motorists.

Table 16: Evolution of the number of commuting trips, travelled commuting distance and commuting trip duration in the different scenarios, compared to the reference scenario, in percentage points.

		Number of trips	Travel distance	Trip duration
S1-TWT	MIV	-17.7	-18.7	-24.6
	Active	-20.3	-17.0	-17.7
	PT	-20.4	-22.0	-21.2
	Total	-19.7	-20.6	-21.2
S4-TWT	MIV	-19.5	-20.7	-26.5
	Active	-21.0	-19.4	-19.9
	PT	-19.2	-20.1	-20.1
	Total	-20.0	-20.2	-21.1
S1-F	MIV	-29.4	-29.8	-37.6
	Active	-32.7	-30.4	-30.5
	PT	-30.3	-30.4	-30.5
	Total	-31.0	-31.0	-32.4
S4-F	MIV	-31.6	-33.3	-39.9
	Active	-33.2	-30.9	-31.0
	PT	-31.8	-33.2	-32.5
	Total	-32.3	-33.0	-33.5

5.6.4 Temporal distribution of trips

The number of trips per hour throughout the day in all five scenarios is depicted in Figure 43. Figure 43a takes all trips into account while Figure 43b only considers commuter trips.

Once again, for a given day of the week – or a given set of days –, the chosen strategy has little to no impact on the observed results. Outside of peak hours, the impact of home office on the number of trips is minimal. For instance, at 3 PM, the number of departures is 3% reduced in the mid-of-the-week scenarios compared to the baseline one. The real effect of home office can be seen when focusing on commuting trips during peak hours: the morning peak, at 7AM, is reduced by 19.1% from Tuesday to Thursday and by 30.3% on Fridays. Similarly, the evening peak (at 5PM) decreases by 17.9% on mid-of-the-week days and by 29.7% on Fridays. The mid-of-the-day peak, at 1PM, is even more impacted: -22.1% from Tuesdays to Thursdays and -34.1% on Fridays.

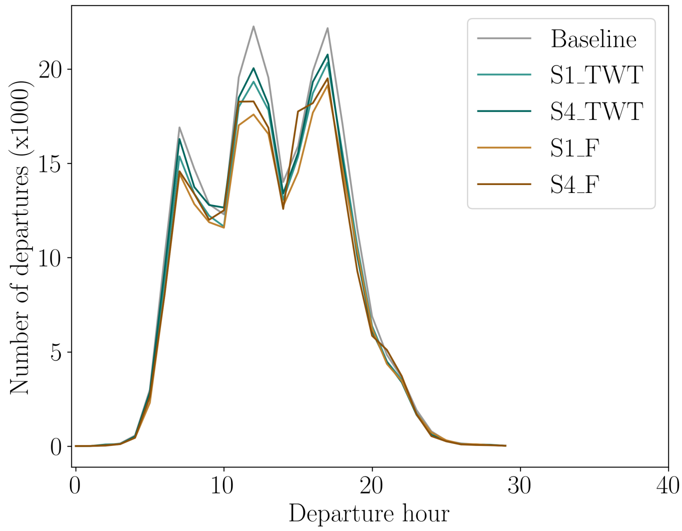
5.6.5 Evolution of car speed during the day

The last paragraphs have shown that, while the number of performed trips is generally reduced by the emergence of home office, car trips seem to be affected on an additional way: their average speed increases due to a reduction of congestion. Speeds of other modes (public transport and active modes) are not (or to a very limited scale) affected by traffic conditions, this is why this paragraph will solely focus on car trips. Moreover, we have seen that the number of trips is more significantly reduced during peak hours compared to off-peak periods.

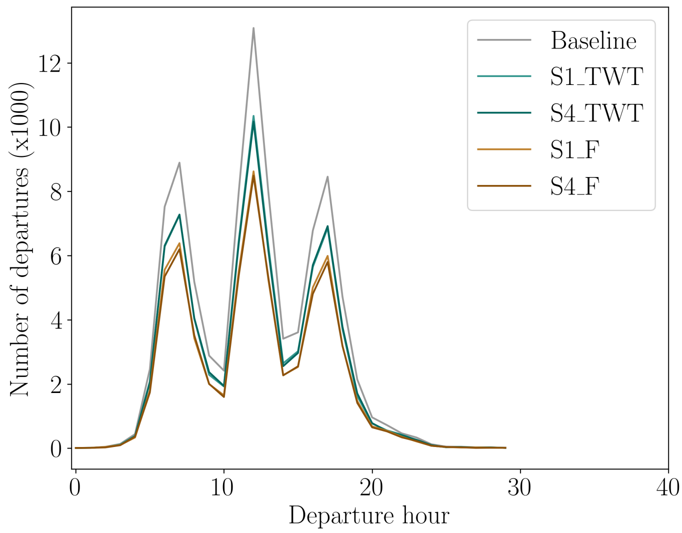
Figure 44 shows the evolution of car speeds throughout the day, observed for all scenarios. Figure 44a depicts this evolution considering all trips, while Figure 44b takes into account only commute trips. The average speed observed on commute trips is generally higher than the one observed without considering the trip purpose.

One can see that similar to what was noticed for the other indicators, there is almost no difference between the two strategies when fixing the day or days of interest. Introducing home office seems to majorly alleviate congestion during peak hours. The drop observed in the average car speed during the morning peak hour in the baseline scenario almost disappears, regardless of the day(s) of interest. During the evening peak hour, a decrease is observed, but the car speeds remain around 2.4 and 3.9 km/h above the baseline level (21.0 km/h), respectively for mid-of-the-week and for Friday scenarios. This trend goes in the same direction as findings from Molloy *et al.* (2021b).

Figure 43: Number of trips per hour throughout the day, considering all trips and commute trips solely.
S1 = strategy 1, S4 = strategy 4, TWT = Tuesday-Wednesday-Thursday scenario, F = Friday scenario, PT = public transport, MIV = motorized individual vehicle, Active = walk and bike.

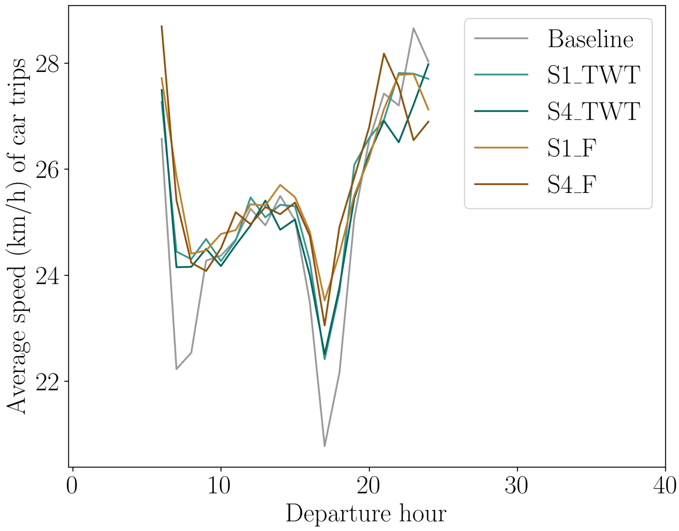


a) All trips

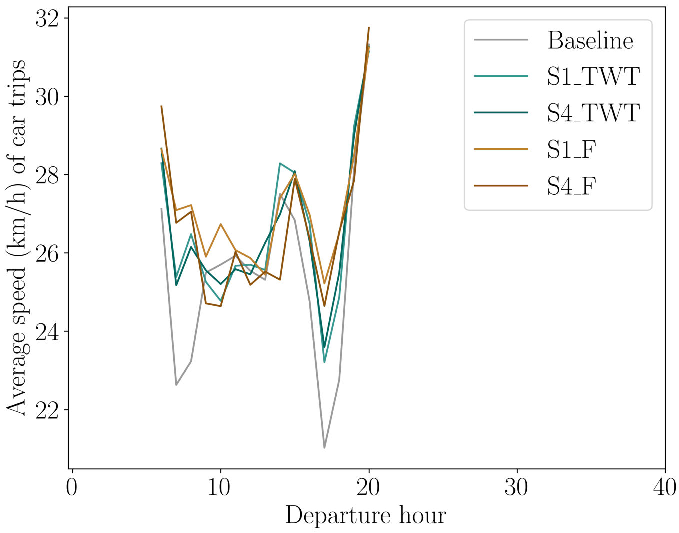


b) Commute trips

Figure 44: Average speed of car trips throughout the days, considering all trips, and commute trips solely.
S1 = strategy 1, S4 = strategy 4, TWT = Tuesday-Wednesday-Thursday scenario, F = Friday scenario, PT = public transport, MIV = motorized individual vehicle, Active = walk and bike.



a) All trips



b) Commute trips

5.7 Conclusion

This chapter presented how models predicting mobility tool ownership and home office behavior were integrated into the travel demand synthesis pipeline `eqasim`. We highlighted how this led us to enrich the population with various attributes. We designed four strategies that all represent different realistic ways agents can adapt their behavior when they are given the possibility to work from home. Two of these strategies were implemented and tested. One of them uses data from the TimeUse+ study to attach a new activity chain, observed in the real life, to each telecommuting agent. The other one represents a lockdown-like situation, in which most of the trips connected to a work activity are cancelled.

No guarantee exists that those strategies *really* represent how an average agent tailors their mobility schedule. Moreover, in a given scenario, only one strategy is applied to all telecommuting agents. The real impact of home office might thus be an average of the simulated impacts of each strategy.

In total, five scenarios were run using the MATSim framework: one baseline or reference scenario, and, for the two implemented strategies, two scenarios representing, on the one hand, an average mid-of-the-week day and, on the other hand, an average Friday. The analysis part of the report compared the variation of key mobility indicators between the scenarios. While the chosen strategy seems to have minimal to negligible effect on the results, the simulated day has a major impact as Friday is much more often chosen as an home office day than any other day of the week. We showed that a significant reduction in the number of trips is achieved, especially during peak hours, while the mode share remains stable, only showing a minor reduction in the share of public transport at the benefit of active modes.

Home office ultimately seems to significantly improve traffic conditions for motorists with an increase in the average observed speeds. This indicates that congestion could be substantially reduced on the major commuting axes.

The implementation of the two remaining strategies will be a key point in the future work on this project. Moreover, we will extend the analysis part so as to focus on the spatial impact of home office.

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