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Abstract

Based on the geo-referenced data, I analyse the commuting behaviour of employees in Germany. With the help of a behavioural economic approach, which is based on the investigation of Simonsohn (2006) for the US, I can show that it is not only the wage and the individual heterogeneity that shape commuting decisions. Instead, the commuting behaviour depends on the context individuals observe in the past. In particular, I demonstrate that the commuting behaviour is influenced by past-observed commutes: Worker choose longer commuting times in a region they just moved to, the longer the average commute was in the region they moved away. This effect applies especially for older employees, but is the same for men and women. Moreover, my robustness checks indicate that individual heterogeneity, selectivity or endogeneity issues do not drive this effect. In addition, I show if individuals stay in the new region, the effect of the previous region disappears, as workers adapt the commuting behaviour of the new region and move again within the new region. This is consistent with the prediction of behavioural economic theory, but refuses the assumption of stable taste differences.

Zusammenfassung

Das vorliegende Papier analysiert auf der Grundlage der georeferenzierten Daten das Pendelverhalten der Beschäftigten in Deutschland. Mit Hilfe eines verhaltensökonomischen Ansatzes, der auf der Studie von Simonsohn (2006) für die USA basiert, kann ich zeigen, dass nicht nur der Lohn und die individuelle Heterogenität die Pendelentscheidung prägen, vielmehr hängt das Pendelverhalten vom Kontext ab, den die Individuen in der Vergangenheit ausgesetzt waren. Insbesondere wird das Pendelverhalten von den in der Vergangenheit beobachteten Pendelzeiten beeinflusst: Beschäftigte entscheiden sich, nach einem Umzug, in eine neue Region, für einen längeren Pendelweg je länger die durchschnittliche Pendelzeit in der Region vor dem Umzug war. Dieser Effekt ist besonders hoch für ältere Beschäftigte, jedoch fällt er für Männer und Frauen gleich stark aus. Meine Ergebnisse sind robust und zeigen, dass weder individuelle Heterogenität noch Selektivität und Endogenitätsprobleme meine Ergebnisse treiben. Zudem verschwindet der Effekt der Region vor dem Umzug, falls Beschäftigte in der neuen Region wohnen bleiben: Beschäftigte ziehen erneut um und passen sich dem Pendelverhalten der neuen Region an. Dies steht im Einklang mit den Vorhersagen der verhaltensökonomischen Theorie, nicht allerdings mit den Annahmen konstanter Präferenzen.

JEL-Classification

J60, R10, R19, R23

Keywords

Commuting, behavioural economic, context effects, movers, geo-referenced data, commuting decision

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1 Introduction

The importance of commuting is rapidly growing – not only the number of commuters but also the distance they commute is continuously rising. How can we explain this commuting behaviour? Not only the growth of urbanization, but also the creation of more employment centres together with the rise of housing prices leads to an increase of commuting. However, the commuting behaviour of individuals can also be explained from a behavioural economic perspective, which is the aim of the following study. In particular, previous research shows that past-observed options can influence individual´s perceptions and therefore their choosing behaviour in subsequent decisions (Simonson and Tversky, 1992). Applied to individual´s commuting behaviour this means that past observed commuting options influence their preferences for commuting and therefore their commuting decisions. This can explain why individuals who move to Munich[1] commute 30 percent less than the average in Munich if they come from regions such as Hof and Coburg, where the average commutes are only 11 minutes. While individuals commute 35 percent more than the average in Munich if they previously lived in regions with an average commuting time over 23 minutes. This indicates that commuting choices are influenced by the context of past-observed commuting options, like the commutes of other persons.

The following study investigates this commuting behaviour, based on the study of Simonsohn (2006) for the US and contributes to the literature in at least three ways: First, I can make use of the geo-referenced employer-employee data. This administrative registry data leads not only to higher validity than survey data, but also provides much more observations and observable characteristics. Second, with the use of this data, I have precise information about individual's residence and workplace location. This allows calculating the exact commuting distance and time of German workers. Third, I can distinguish between movers of different resident types like rural areas, small and large towns, cities as well as metropolitan cities. For which I can determine movers of these different kinds of regions.

When individuals choose between residences they face the difficult decision of how far they are willing to commute, weighting the benefits and costs of commuting. Advantages of commuting may arise through cheaper rents and housing prices outside the city centre resulting in a higher disposable income. Furthermore, commuting can provide individuals a job opportunity, since persons who live in smaller rural areas may have no or no adequate employment offer. However, commuting also leads to disadvantages; it takes time, causes stress and intervenes the relationship between work and family. Thus, has a negative effect on the well-being of individuals (Frey and Stutzer, 2007). To decide how far individuals want to commute, they have to trade-off the benefits with the disutility of commuting. Indeed, costs and benefits do not have the same effect on utility: The reaction to losses is stronger than the reaction to corresponding profits (loss aversion, Kahneman and Tversky, 1979). In the context of commuting decisions, however, Dauth and Haller (2020) show no sign of loss aversion, which contradicts previous experimental evidence (Tversky and Kahnemann, 1991).

[1] Provincial capital Munich with an average commuting time of 17.5 minutes. This average commuting time is calculated from a restriction of the commuting time from 2 to 90 minutes (see chapter 3.1).

Empirical evidence from urban economics shows the disutility of commuting for which individuals want to be compensated. For the Netherlands, Van Ommeren et al. (2000) and Van Ommeren (2005) find a marginal willingness to pay for an additional kilometre of commuting of 0.15 Euro per day or 17 Euro for one additional hour of commuting (Van Ommeren and Fosgerau, 2009). With regard to a compensation by the employer, Heuermann et al. (2016) investigate that employers compensate only a few employees directly for additional commuting costs. Hence, the commuting choice is mainly an individual decision, which can be strongly influenced by prior experiences.

However, individuals are often not able to assess the disutility of commuting correctly, and they are often uncertain about their preferences, which contradicts the standard economic theory (Kahneman and Tversky, 1979). Instead, individuals construct their preferences when needed, for instance when making choices (Bettman et al., 1998). For example, in the context of commuting decisions, persons rely on a wide range of possible cues, like the commutes of other persons. Moreover, in the literature of decision-making (Bettman et al., 1998; Huber et al., 1982) it becomes fundamental that individual´s decision can be influenced by the context: Individuals interpret information by comparing it not only with other available options, but also with what has recently been observed. Following Hartzmark and Shue (2017), these context effects have the potential to affect a variety of important real-world decisions. They distort not only judicial perceptions of the severity of crimes, leading to unfair sentencing, but also effect employee hiring, medical diagnose as well as housing and commuting decisions.

The context effect, which is relevant for this study, is the *Background Context Effect.* Accordingly, choices depend on options countered in the past – preferences can change with the history of choices. The intuition behind is that the same product may seem more attractive against the background of less attractive alternatives and unattractive on the background of more attractive alternatives (Simonson and Tversky, 1992). Simonson and Tversky (1992) document this effect in an experiment: Two stages in which subjects have to make choices in sequence. In the first stage, half of the subjects are confronted with two options that have a relative high cost for an attribute and the other half should make a choice with a relative low cost for the same attribute. In the second stage, all subjects are confronted with the same choice. In line with the Background Context Effect, subjects who are confronted with a relative high cost for an attribute in the first stage are more likely to choose the more expensive option in the second stage, because it appears cheaper to them.

However, there is ample evidence of the Background Context Effect. Bhargava and Fisman (2014) demonstrate this effect in the context of speed dating. They show that the attractiveness of former partners reduce the probability of a date. Moreover, Hartzmark and Shue (2017) demonstrate that today´s earnings impresses investors more when previous earnings have been poor. Furthermore, Simonsohn and Loewenstein (2006) present the effect in housing choices: Individuals who move from cities with relative high housing costs are more likely to pay higher prices in the new city compared to those individuals coming from cities with cheaper markets. Applied to the commuting behaviour, this means that commuting options, persons face in the past, affect the current commuting decision of these people. However, relative little research has examined when and why the Background Context Effect influences commuting decisions. The only study comes from Simonsohn (2006). He considers movers between two metropolitan areas in the US and takes the average commuting time of the previous city as a proxy for past-observed commuting options. To examine how previous observed commutes influence commuting decisions after moving to a new city. He finds that individuals choose longer commutes in the new city, the longer the average commute was in the city they came from. Commuting decisions are thus influenced by commuting options individuals face in the past, which is in line with the Background Context Effect.

The following study is based on the investigation of Simonsohn (2006). By considering employees who relocate between NUTS-3 regions in Germany, I examine the context effect for Germany. The results are consistent with those of Simonsohn (2006). They show that individuals coming from backgrounds with higher commuting times choose initially higher individual commutes in the destination region compared to individuals coming from regions with lower commutes. In contrast to Simonsohn (2006), I differ between movers who relocate between urban and rural areas. Therefore I show the presence of a context effect only for movers, who relocate to urban regions. For movers to rural areas past-observed commuting options have no effect on commuting choices. Moreover, I confirm these results on a smaller regional level – for movers between municipalities. However, for movers between labour market regions I find no significant effect of the context. This results because past-observed commuting options influence only workers who relocate between two urban regions and from rural to urban areas. As labour market regions include both areas and as the average drive time is calculated for each labour market region, the effect could be cancelled out. In addition, the robustness checks show that there is only little space for unobserved heterogeneity, selectivity and endogeneity issues. Moreover, I find no sign of stable taste difference as traditional economic theory would indicate.

2 Theoretical Motivation for the Background Context Effect

As empiric shows, decisions are preference dependent. These preferences however change with past-observed options. As Tversky and Simonson (1992) demonstrate in their background contrast experiment, previous experiences of individuals influence their perceptions and therefore their choice behaviour in subsequent decisions. For commuting decisions, this implies that previous faced commuting options affect current commuting preferences and thus the commuting behaviour of individuals. The following approach is based on this concept, which is also used by Simonsohn (2006). The idea is that the disutility of commuting decreases when a person is only confronted with longer commuting options in the past. Whereas, the disutility increases when individuals are only exposed to short commutes.

To investigate this approach and to measure the effect of the context, I use a relocation, where individuals have to move between two NUTS-3 regions in Germany. According to the background contrast experiment of Tversky and Simonson (1992), the commuting behaviour after the movement should be affected by previous observed commuting options. This concept is formally represented as:

$$\alpha_t^* = (1-\beta)\alpha_{t-1} + \beta(\alpha_t) \qquad \beta \in [0,1] \qquad (1)$$

Abstracting all other influences, α_t^* represents the individually chosen commuting time of an individual as a weighted sum of present and past observed commuting options, with the weights declining exponentially into the past (Ryder and Heal, 1973). More precisely, under the assumption of $\beta = 1$ there is no impact of past-observed commutes on the current commuting time, since $\alpha_t^* = \alpha_t$ and thus no impact of the context. In contrast, if $\beta = 0$ the current commuting preferences are only determined by the previous observed commuting time, corresponding in $\alpha_t^* = \alpha_{t-1}$.

In the following, I expect that β takes values between 0 and 1 $(0 < \beta < 1)$, so that two identical individuals with different levels of previous observed commuting options have a different level of α_t^*, when moving to the same region. Moreover, I use the average commuting time of the region before the move as a proxy for previous observed commuting options. According to equation (1), individuals moving from regions with higher average commutes choose higher individual commuting times (α_t^*) in the destination region compared to individuals coming from regions with lower average commuting times. This will be the first prediction I investigate in this paper:

1. The average commuting time of the region a person moves away has a positive influence on the individually selected commuting time in the destination region.

If individuals however stay in the new region and observe the commuting options of the new region their preferences for commuting change due to the new observed commutes of the new region. This leads to a change of the desired commuting length. For example, movers who relocate from regions with higher commutes to regions with shorter commuting times have at first a higher tolerance for long commutes and prefer cheaper and more living space outside the city centre. Therefore, they initially commute longer than the average in the new region. However, if they stay in this region and observe lower commutes, preferences for shorter commutes rise and the disutility for commuting increases. Thus, they get dissatisfied with their initial chosen commutes and might move again within the new region to reduce their initial chosen commuting time, which corrects an original overspending of commuting. This relation is illustrated by the second prediction:

2. Individuals readjust their commuting times and move again, when staying in the new region.

The second prediction is therefore useful in ruling out explanations based on stable unobserved differences across individuals who move from different regions. Because if individuals who come from regions with higher average commutes, travel more after the movement because they are different from those who come from regions with lower average commutes, I would not expect them to revise their commutes by moving again.

3 Empirical Approach and Data

3.1 Data

For the analysis, I use the employment biographies of a 6 percent random sample of all German workers subject to social security contribution. The administrative registry data cannot account for self-employed or civil servants, however, it covers more than 80 percent of the German labour force. The Integrated Employment Biographies (BeH – Beschäftigenhistorik V10.01.00, 2016) by the

Institute for Employment Research (IAB) offers exact information about the time in an employment as based the status reports for the pension insurance. Besides the socio-demographic characteristics, information on the firm level are included, which comes from the Establishment History Panel (BHP). This dataset contains information about the branch of industry, the establishment location, number of employees and marginal part-time employees by gender, age, occupational status, nationality and qualification. As daily wages are top-coded at the social security contribution ceiling, I use the imputation procedure from Card et al. (2013) to recover wages above this threshold.

A unique feature of this database is the supplement IEB GEO, which offers anonymized address information in the form of geocodes for the individual's residence location as well as the place of the employer for the years 2000 to 2014. With this address information, exact individual driving time is calculated based on the road network released by OpenStreetMap. Using the road routing algorithm by Huber and Rust (2016) the exact door-to-door commuting time is calculated. Nevertheless, only distances for drivers can be determined, those for users of public transport may differ. However, the car represents the most important mean of transport. Almost 70 percent of workers use the car on the way to work. Whereas only 14 percent of commuters use the public transport system.

With the use of geocodes, the commuting time is not limited by administrative units, which reduces measurement error for individuals close to administrative borders and mitigates the problem of spatial sorting within areas. Still, using the driving time can cause issues regarding the experienced commuting time: The algorithm cannot recognize dense traffic in the daily rush hours. Nevertheless, as the time is measured before and after the regional move, the change of the time might be less affected by this measurement problem.

In the following study, I investigate the commuting behaviour of German employees, excluding marginal employment as well as employees older than 57 and younger than 18 years. In line with Simonsohn (2006), I consider only workers who commute more than 2 and less than 90 minutes. This excludes not only long-distance and weekend commuters but also individuals who have a very short commuting way to work.

To test prediction 1, I restrict the sample to employees who relocate between two NUTS-3 regions in Germany. In particular, they have to change their place of work as well as their place of residence between 402 German NUTS-3 regions. This guarantees a relocation of the entire centre of live. Thereby I keep the NUTS-3 region of the place of work and the place of residence constant for two years before and after the move. This guarantees that movers are able to adopt commuting options as well as the commuting behaviour of the region they lived in. In addition, with this assumption, it is possible that movers can relocate again within the target region to readjust their initial chosen commuting time. Furthermore, time periods are categorized to t-1 for the year before the movement, t=0 for the year of the relocation and t=+1 for the year after the movement.

To test prediction 2, I consider re-movers. These are employees who relocate again within the new region in period t=+1 (one year after the movement), holding the place of work constant.

3.2 Identification Strategy

To test the first prediction I estimate how the average commuting time of the region before the movement influences the individually chosen commuting time in the target region using cross sectional OLS:

$$\ln\left(C_{i,t=0}\right) = \beta_0 + \beta_1 X'_{i,t=0} + \beta_2 \ln\left(\bar{C}_{i,t-1}\right) + \ln\left(C_{i,t-1}\right) + \varepsilon_{i,t=0} \quad (2)$$

Where $\ln(C_{i,t=0})$ represents the dependent variable, the logarithm of the individual chosen commute in minutes after the relocation (t=0). As independent variable I include $\ln\left(C_{i,t-1}\right)$ the logarithm of the individual commuting time of the previous region (t=-1) and $X'_{i,t=0}$ as a vector of control variables. This vector includes the log wage, calendar years, occupational status and indicator variables for firm size (number of employees, 4 categories), age group (4 categories), occupation (12 categories), industry (9 categories) and residence place type as well as working place type (5 categories). These types represent whether individuals live and work in a metropolitan city, city, large town, small town or in a rural area. Moreover, $X'_{i,t=0}$ incorporates several dummies indicating whether a worker is a supervisor, has a leading position, is a trained/professional, specialist/expert or has an auxiliary activity. In addition, $X'_{i,t=0}$ corporates a dummy for women, migrants, West Germany and for being low skilled (without vocational training) medium skilled (with vocational training) and high skilled (academic degree). Furthermore,$(\bar{C}_{i,t-1})$ demonstrates the variable of interest, the logarithm of the average commuting time of the region before the relocation (t=-1). This average drive time is calculated for each NUTS-3 region and represents the context of past-observed commutes.

According to prediction 1, β_2 of equation 2 should be positive. Because individuals with higher observed commuting backgrounds have a lower disutility of commuting and thus prefer living outside the city center facing higher commutes.

However, in the case of *unobserved heterogeneity* that can influence the estimates of $\bar{C}_{i,t-1}$ and *sorting* – meaning that movers move to certain regions because of their taste for commuting – my results would not be valid. To face the issue of unobserved heterogeneity I exclude all observable individual and firm characteristics in my analysis. Moreover, I have to assume that the unobservable factors have the same effect on the estimation of $\bar{C}_{i,t-1}$ than the observable ones. So when estimating the same effect of $\bar{C}_{i,t-1}$ with and without any observable factors this leaves only little room for the issue of unobserved heterogeneity.

Another issue is sorting: For example, individuals who dislike (like) commuting choose regions with lower (higher) commuting times. To face this selectivity issue I do not only include the individual own drive time of the region before the movement $C_{i,t-1}$ (see equation 2), but I also do a robustness check: In line with selectivity individuals select themselves in region because of their commuting taste. If people select themselves in regions with higher average commutes because of their taste for high commuting they should also have commuted longer in the region before the movement. To exploit this fact I do a reversed regression in which I regress the individual commute in the previous region on the average commuting time of the target region – after the movement.

$$\ln(\bar{C}_{i,t-1}) = \beta_0 + \beta_1 X'_{i,t=0} + \beta_2 \ln(C_{i,t=0}) + \varepsilon_{i,t=0} \quad (3)$$

In line with selectivity, I should find a positive effect of the average commutes in the destination region on the individuals commuting time in the region before the movement.

The results of the unobserved heterogeneity und sorting issue are presented in the robustness checks in chapter 4.3.

To test prediction 2, I restrict the sample to workers who move again within the new region, one period after the first move (t+1). I use the following identification strategy, where only changes are analysed. Because of these differences, individual fixed effects are cancelled out:

$$\Delta \ln(C_{i,t+1}) = \beta_1 \Delta W_{i,t+1} + \beta_2 ln\big(\bar{C}_{i,t=0} - \bar{C}_{i,t-1}\big) + \Delta \varepsilon_{i,t+1} \quad (4)$$

The dependent variable $\Delta \ln(C_{i,t+1})$ is the change of the individual chosen commuting time after the second and the first move within the new region. The control variable is the change in wages ($\Delta W_{i,t+1}$) between the second and the first move. And the key predictor is represented by the difference between the observed commuting time in the new region (t=0) and the region before the movement (t=-1), corresponding in $ln\big(\bar{C}_{i,t=0} - \bar{C}_{i,t-1}\big)$. This classification of the reference point presupposes that the perceptions of employees have fully adjusted after one period.

However, this might still be no correct estimate of the change of the commuting time because workers might endogenously choose whether to move a second time. Therefore, I use a two-stage Heckman selection method (Heckman, 1979). Specify where at first I account for the decision of moving a second time, which can be estimated as a latent variable model:

$$P_i^* = \delta_1 S_i + \varepsilon_i \quad (5)$$

With the decision to move a second time by:

$$P_i = \begin{cases} 1 & if \quad P_i^* > 0 \\ 0 & otherwise \end{cases} \quad (6)$$

P_i^* shows the latent variable for the propensity to move a second time within the target region and S_i is a vector of socio-demographic characteristics and information on industry and firm size, which influence individual i. To estimate whether or not a worker moves again I use a probit estimation. These results are then taken to construct an Inverse Mills Ratio. This Inverse Mills Ratio is then included in the second step equation to correct for selection bias.

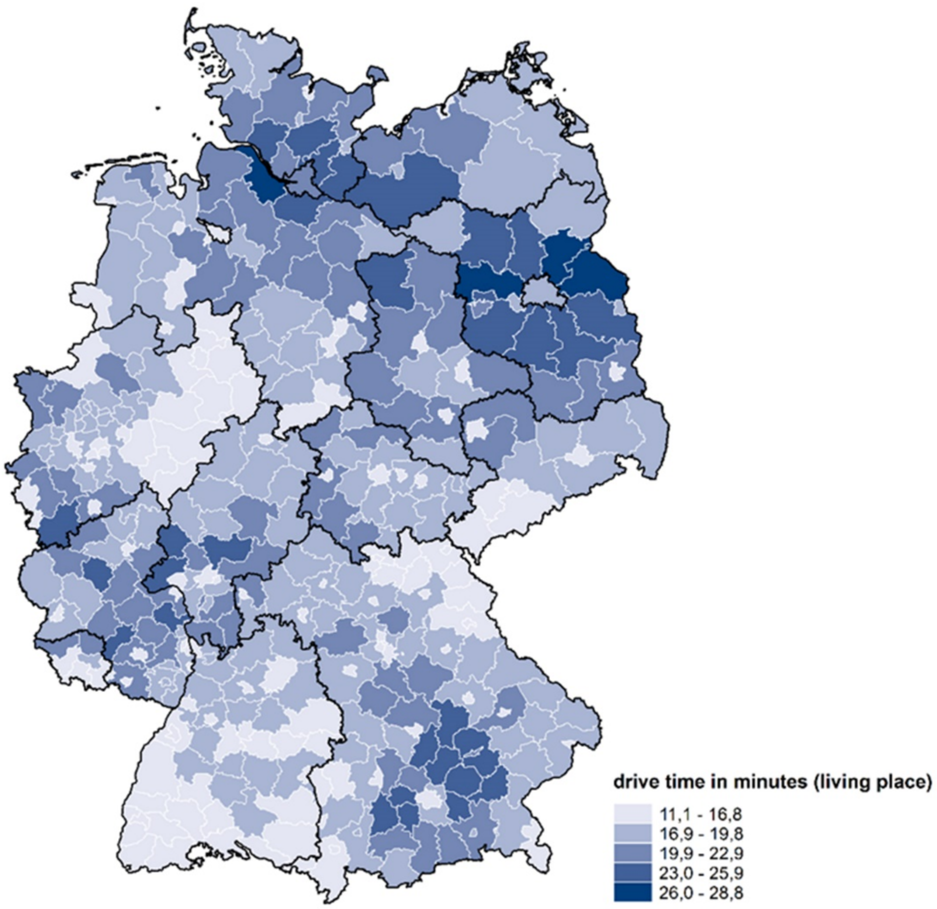
If workers decide to move for a second time within the new region, according to prediction 2, the coefficient β_2 (equation 4), should be positive: Individuals coming from regions with high observed commutes to a new region (with less average commutes) commute at first too long. This leads to a change of the desired commuting lengths. Therefore, if they move again within this new region they reduce their commutes and adopt the commuting behaviour of the new region.

4 Empirical Analysis of the commuting behaviour

4.1 Descriptive Statistics

Figure 1 presents the distribution of the average commuting times for the place of residence for each NUTS-3 region in Germany[2]. Workers living in metropolitan cities, like Munich, Berlin, Frankfurt and Bremen have a lower average commuting time than those in the surrounding regions. In particular, the average commuting time in metropolitan cities is 16.8 minutes, while workers in rural areas commute on average almost 20 minutes to work. This implies that workers who live in large cities will most likely work there as well. While employees living in the suburbs travel from the surrounding regions into the city centre to work. Possibly, for the reason that job opportunities are better in the city centre and housing costs are cheaper in the suburbs.

Figure 1: Regional distribution of the commuting time



Source: Own calculation based on BeH V10.01.00.

[2] Whereby the drive time is restricted between 2 and 90 minutes (see chapter 3.1).

Figure 1 illustrates the mean commuting time of workers place of residence by NUTS-3 regions in Germany, whereby the drive time is restricted between 2 and 90 minutes. Dividing the average drive time in 5 categories I find lower commuting times in larger cities, like Munich, Berlin and Frankfurt and higher in smaller cities.

Comparison of movers and non-movers

To demonstrate how the characteristics differ from workers who relocate from those who do not, I compare both groups. In particular, I compare summary statistics for movers before the movement and workers who do not move.

Table 1: Summary statistics of main variables

Variable	Movers	Non-movers
Woman	49.31 (0.50)	44.13 (0.50)
Migrant	4.38 (0.20)	6.37 (0.24)
West	82.95 (0.38)	81.57 (0.39)
Age groups		
18-25	19.74	10.83
25-34	46.99	22.96
35-44	24.53	31.19
45-56	8.73	35.02
Education		
Low-skilled	15.80 (0.36)	12.55 (0.33)
Medium-skilled	58.70 (049)	70.22 (0.46)
High-skilled	24.25 (0.43)	12.55 (0.35)
Industry		
Primary sector	1.86	3.00
Food manuf.	1.99	2.37
Consumer goods	2.07	2.60
Industrial goods	5.25	9.27
Capital goods	7.81	11.55
Construction	3.88	5.98
Personal services	21.70	19.64
Business services	27.93	22.06
Public sector	27.51	23.52
Occupation		
Agricultural workers	0.95	1.21
Lower manual occupations	5.75	12.27
Higher manual occupations	9.92	14.80
Technicians	4.98	5.25
Engineers	6.29	2.98
Lower services	7.23	11.96
Higher services	7.04	5.72
Semi-Professionals	10.62	9.08
Professionals	5.90	1.97
Lower administrative occupations	7.24	8.11
Higher administrative occupations	27.14	22.93
Managers	4.99	3.07
Supervisor	2.55	2.10
Leading position	0.25	0.72
Specialist/expert	31.68	20.42
Trained/professional assistant	64.10	70.93
auxiliary activity	2.48	6.63
Firm size		
0-9	15.02	13.34
10-49	26.39	24.58
50-249	28.15	28.72
250-499	9.49	10.95
>500	20.95	22.42
N	14,745	20,369,020

Notes: Means and standard deviation (in parentheses) of main variables. Comparison of movers and non-movers before the movement in t=-1.

Source: Own calculation based on BeH V10.01.00.

Table 1 shows that movers and non-movers vary in their productivity-related characteristics: Employees who relocate are more qualified (academic degree) than non-movers. Regarding industry, the share of workers who relocate is higher in personal (21.7 percent) and business services (27.93 percent) as well as in the public sector (27.51 percent). Moreover, the share of employees working as engineers (6.29 percent), semi-professionals (10.62 percent), professionals (5.9 percent), managers (4.99 percent) and in higher services (7.04 percent) as well as in higher administrative occupations (27.14 percent) is higher for movers than non-movers. Differences also become obvious in the age groups. While the share of movers is much higher between 18 and 34 (19.74 percent), non-movers are mainly between 35 and 56 years old (66.21 percent). This comparison shows therefore considerable heterogeneity between movers and non-movers. This becomes also apparent considering the difference between the drive time of movers and non-movers.

Table 2: Summary statistics of the wage and the drive time

	Variable	Mean	Std. dev.	25th Perc.	50th Perc.	75th Perc.	N
Movers	Drive time	19.55	16.64	7.63	14.55	25.93	14,745
Non-Movers	Drive time	18.19	14.61	7.80	14.25	23.93	20,369,020
Movers	Wage	86.25	55.38	50.13	74.88	107.33	14,745
Non-Movers	Wage	86.56	54.91	50.63	77.13	106.36	20,369,020

Notes: Means, standard deviation, 25th, 50th, 75th percentiles of the drive time and the wage. Comparison of movers and non-movers before the movement in t=-1.

Source: Own calculation based on BeH V10.01.00.

While daily wages of movers and non-movers are almost the same, movers tend to drive on average 1.36 minutes longer to work than non-movers. Movers, therefore, have a higher willingness to commute.

Comparison of movers before and after the movement

In the following, I consider summary statistics of workers who move. The next table (Table 3) shows the difference between the drive time and the wage of movers before (t=-1) and after the relocation (t=0).

Table 3: Summary statistics of the wage and the drive time

Variable	Mean	Std. dev.	25th Perc.	50th Perc	75th Perc.
Drive time (t=-1)	19.55	16.64	7.63	14.55	25.93
Δ Drive time (t=0)	+3.74	23.77	-8.22	2.52	14.72
Wage (t=-1)	86.25	55.38	50.13	74.88	107.33
Δ Wage (t=0)	+12.82	40.74	-2.59	8.59	27.11
N	14,745				

Notes: Means, standard deviation, 25th, 50th, 75th percentiles of the drive time and the wage. Comparison of movers before and after the movement.

Source: Own calculation based on BeH V10.01.00.

The average mover experiences an increase in wages (+12.83 Euros per day), which supports the intuition that employees are more likely to move if they can realize an increase in wages. Not only wages rise due to the movement, but also the commuting time. On average, the commuting time increase by 3.74 minutes. In addition, the share of employees working and living in metropolitan cities increases of about 3.83 and 2.95 percentage points after the movement, whereas the share of workers living and working in small towns and rural areas decreases (see Appendix A). This confirms the attractiveness of large cities and the ongoing urbanization.

Motivation of movers

As already mentioned, when workers move to a new region they experience an increase in wages, which could be an important point in terms of the reason for moving. Furthermore, Table 4 shows that almost 41 percent of workers change their occupation after the movement. In addition, more than 34 percent of movers work in a different industry.

Table 4: Summary statistics of changes in occupation, industry and promotion

	Occupation	Industry	Promotion
Change in percent	40.84	34.40	12.90
N	6,022	5,073	1,902

Notes: Percent of workers who change occupation, industry or promotion after the movement (t=0). Own calculation based on BeH V10.01.00.

Workers therefore might especially move for job related reasons. Simonsohn (2016) represents a similar finding. He reports that more than 36 percent of individuals in the US move for job related reasons. Moreover, in many cases (12.9 percent) the movement is related with a promotion, like a promotion from trained/professional assistant to specialist/expert (see Table 4).

Comparison of movers and re-movers

In the following, I take a closer look at re-movers. Re-movers are workers who relocate a second time within the new region. Table 5 compares these re-movers with the share of movers (workers who move one time) after the first and before the second movement.

Table 5: Summary statistics of main variables

	Movers	Re-Movers
Woman	50.04 (0.50)	47.47 (0.50)
Migrant	3.78 (0.04)	4.29 (0.20)
West	86.50 (0.34)	88.87 (0.31)
Age groups		
18-24	14.20	18.00
25-34	48.30	46.99
35-44	26.87	24.95
45-56	10.63	10.06
Education		
Low-skilled	6.39	7.92
Medium-skilled	62.45	67.43
High-skilled	30.55	23.82
N	10,757	3,988

Notes: Means and standard deviation (in parentheses) of main variables. Comparison of movers and re-movers after the first movement (t=0).

Source: Own calculation based on BeH V10.01.00.

From 14,745 movers in t=0 3,988 relocate a second time in t=1. Especially medium-skilled workers, tend to re-move within the new region. In addition, the share of men and employees in West Germany is higher for re-movers. Furthermore, re-movers are on average younger (between 18 and 24 years).

Table 6 shows the difference between daily wages and the drive time of movers and re-movers after the first relocation (t=0).

Table 6: Summary statistics of the drive time and the wage

	Variable	Mean	Std. dev.	25th Perc.	50th Perc	75th Perc.	N
Movers	Drive time	19.43	15.42	8.32	15.28	25.62	10,757
Re-Movers	Drive time	33.75	22.42	15.75	28.58	48.22	3,988
Movers	Wage	100.22	58.15	62.40	85.28	123.04	10,757
Re-Movers	Wage	96.24	54.00	63.19	82.66	114.64	3,988

Notes: Means, standard deviation, 25th, 50th, 75th percentiles of the drive time and the wage. Comparison of movers and re-movers after the first movement (t=0).

Source: Own calculation based on BeH V10.01.00.

Compared to movers, the drive time of re-movers is much higher after the first movement in t=0. Employees who move only one time have a drive time of 19.43 minutes in t=0, while re-movers drive over 14 minutes longer to work after the first relocation. This results not only from the fact that re-movers compared to movers come from previous regions with longer commutes, but re-movers also rather move from rural regions with higher average commuting times. According to the Background Context Effect this leads to a higher tolerance for commuting and thus to a higher chosen individual commuting time after the movement. This could explain why especially these employees move again in the new region and reduce their commuting time by more than 13 minutes (see Table 7).

Table 7: Summary statistics of the drive time and the wage

Variable	Mean	Std. dev.	25th Perc.	50th Perc	75th Perc.
Drive time (t=-1)	20.69	17.24	8.30	15.63	27.30
Δ Drive time (t=0)	+13.06	27.59	-3.02	10.45	29.42
Δ Drive time (t=+1)	-13.07	24.52	-27.37	6.14	2.38
Wage (t=-1)	82.00	51.09	47.81	72.80	102.53
Δ Wage (t=0)	+14.15	36.41	-0.58	9.18	27.67
Δ Wage (t=+1)	+6.5.00	28.83	0.18	3.65	9.09
N			3,988		

Notes: Means, standard deviation, 25th, 50th, 75th percentiles of the drive time and the wage. Comparison of re-movers before and after the first movement and after the second move.
Source: Own calculation based on BeH V10.01.00.

Table 7 shows the difference in wages and the drive time before the first move (t=-1) after the first move (t=0) and after the second move (t=+1) for re-movers. As explained before the increase of the drive time after the first movement is much higher for re-movers than for movers. Re-movers increase their drive time by over 13 minutes in t=0. In the same amount, they shorten their driving time after the second relocation in t=1. This corrects an original overspending of commuting and indicates prediction 2.

4.2 Empirical Analysis

Prediction 1: Own selected commuting time after the movement

In the following, I test the first prediction, in which I investigate how the average commuting time of the region before the movement influence the individually selected commuting time in the target region (see equation 2). Because of heteroscedasticity, clustered standard errors are used[3]. Table 8 shows the results of 5 specifications.

[3] Standard errors are clustered by NUTS-3 regions, movers live in.

Table 8: **Individually selected commuting time after the movement**

NUTS-3 region	Dependent variable: Log($C_{i,t=0}$)				
	Model 1	Model 2	Model 3	Model 4	Model 5
Log ($\bar{C}_{i,t=0}$)	0.630***	0.586***	0.591***	0.590***	0.594***
	(0.068)	(0.070)	(0.069)	(0.069)	(0.068)
Age groups	Yes	Yes	Yes	Yes	Yes
Log (wage)	0.071***	0.072***	0.065***	0.064***	
	(0.025)	(0. 024)	(0. 024)	(0.024)	
Woman	-0.037*	-0.037*	-0.032	-0.031	-0.042**
	(0.019)	(0.019)	(0.019)	(0.019)	(-0.02)
High skilled	-0.070**	-0.068*	-0.073**	-0.074**	-0.058*
	(0.034)	(0.035)	(0.035)	(0.035)	(0.034)
Medium skilled	-0.029	-0.031	-0.035	-0.035	-0.034
	(0. 0.030)	(0.030)	(0.030)	(0.030)	(0.031)
Occupation dummies	Yes	Yes	Yes	Yes	
Industry dummies	Yes	Yes	Yes	Yes	
Dummy migrant	-0.057	-0.051	-0.046	-0.046	-0.049
	(0.039)	(0.039)	(0.038)	(0.038)	(0.038)
Supervisor	-0.045	-0.044	-0.043	-0.042	-0.036
	(-0.047)	(-0.047)	(-0.047)	(-0.047)	(-0.047)
Leading position	-0.074	-0.074	-0.074	-0.074	-0.06
	(-0.07)	(-0.07)	(-0.068)	(-0.069)	(-0.068)
Specialist/expert	0.039	0.045	0.044	0.045	0.06
	(-0.044)	(-0.044)	(-0.043)	(-0.043)	(-0.043)
Trained/professional assistant	0.031	0.036	0.039	0.04	0.05
	(-0.038)	(-0.038)	(-0.038)	(-0.038)	(-0.038)
Occupational status	Yes	Yes	Yes	Yes	Yes
Firm size (Number of workers)	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Residence place type	Yes	Yes	Yes	Yes	Yes
Working place type	Yes	Yes	Yes	Yes	Yes
West	0.018	0.019	0.017	0.017	0.027
	(0.040)	(0.039)	(0.037)	(0.037)	(0.035)
Log($\bar{C}_{i,t-1}$)		**0.240*** **	**0.163*** **	**0.161*** **	**0.159*** **
		(0.058)	**(0.059)**	**(0.059)**	**(0.059)**
Log($C_{i,t-1}$)			0.080***	0.039*	0.039*
			(0.009)	(0.023)	(0.023)
Log($C_{i,t-2}$)				0.044*	0.045**
				(0.023)	(0.023)
Constant	0.563*	-0.014	0.03	0.025	0.169
	(-0.289)	(0. 308)	(0.308)	(0.307)	(0.309)
N	14,745	14,745	14,745	14,745	14,745
R^2	0.0487	0.0504	0.0564	0.0567	0.0561
Adj. R^2	0.0444	0.0461	0.0521	0.0523	0.0518

Notes: The table reports regressions of the individually selected log commuting time after the first relocation on the average log commuting time of the region before the movement and control variables. Standard errors clustered by NUTS-3 regions, below parameter estimates. Levels of significance: *1%, **5%, ***10%.

Source: Own calculation based on BeH V10.01.00.

According to model 1, which includes individual and firm characteristics, the mean commuting time of the place of residence in the destination NUTS-3 region (in t=0) has a positive influence on the individual chosen commuting time. In addition, the wage has a positive significant effect, which might be the result of compensatory wages for longer commutes as shown by Mulalic et al. (2013. In contrast, being a female has a negative influence on the individual chosen commuting time in the target NUTS-3 region. Chen and McQuaid (2012) also investigate this negative relationship for the UK.

Model 2 incorporates the average travel time of the place of residence of the previous region ($\bar{C}_{i,t-1}$) as a proxy for past-observed commuting options. Consistent with the first prediction, model 2 shows a positive significant effect on the individual commuting time. Moreover, the effect can be interpreted as causal, as I can exclude selectivity, unobserved heterogeneity and endogeneity issues (see chapter 4.3). Hence, mobile workers coming from NUTS-3 regions with higher observed commutes have a higher tolerance for commuting and choose longer individual commutes in the target region. This indicates the presence of a context effect and is therefore consistent with the result of Simonsohn (2006).

In addition, model 3 controls for unobserved heterogeneity across individuals by including information from previous individual commuting choices ($C_{i,t-1}$). A significant and positive effect on the commuting time in the destination region can be observed. Moreover, adding this variable, the effect of the key variable of interest $\bar{C}_{i,t-1}$ gets smaller, but remains positive and significant. Comparing both coefficients ($C_{i,t-1}$ and $\bar{C}_{i,t-1}$) shows that the effect of the context is twice as high as the effect of the own previous drive time.

In model 4, the individual commuting time two periods before the relocation $C_{i,t-2}$ as an additional control is added. Nevertheless, $\bar{C}_{i,t-1}$ remains positive and significant even with the inclusion of the drive time two periods before the movement.

Since commuting may be endogenous with respect to wages, model 5 excludes daily wages, which hardly changes the size of the coefficient of $\bar{C}_{i,t-1}$.

Thus, the results show that the current commuting behaviour of employees is not only affected by their own previous drive time but also by the average commuting time of the region, they moved away.

Prediction 2: Readjusting the commuting time

If workers relocate from regions with higher commutes to regions with shorter commuting times ($\bar{C}_{i,t-1}$>$\bar{C}_{i,t=0}$), they initially commute longer than the average in the target region[4]. The reason is that they have a higher tolerance for commuting as they come from regions with long commutes. Nevertheless, if they stay in the new region and observe less commutes they get dissatisfied with their initial chosen commutes and their desired commuting time change. Therefore, I expect that they decrease their commutes by relocating again within the new region.

To investigate the adjustment of the commuting times after a second movement, I consider only individuals who move again one year after arriving at the new region. In total 3,988 individuals move again within the new NUTS-3 region in t=1.

The regression estimate of (equation 4) is presented in Table 9, where $\left(C_{i,t+1} - C_{i,t=0}\right)$, the dependent variable, measures the change of the individual commuting time. Therefore represents

[4] Employees moving from previous regions with more than 23 minutes, commute 35 percent more than the average in the target region.

the adjustment of the individual commuting time between t=0 and t=+1. The key predictor is the difference between the average commuting time in the new region and the previous region ($\bar{C}_{i,t=0} - \bar{C}_{i,t-1}$). Moreover, as workers may endogenously choose whether to move a second time I use a two-step regression (Heckman, 1979): In the first stage, I estimate a probit regression for the choice of a second movement in the new region (equation 5). The result of this probit regression can be seen in Appendix B. They show e.g. the higher the difference between the average commuting time and the own selected drive time in the target region, the more likely is a second movement. In the second stage, I use the inverse Mill´s ratio from the first stage as an additional control variable. The results are presented in Table 9 and show in line with prediction 2, the higher the difference between the new and the old region ($\bar{C}_{i,t=0} - \bar{C}_{i,t-1}$) the higher is the adjustment of the individually chosen commuting time after the second move. The coefficient of($\boldsymbol{\bar{C}_{i,t=0} - \bar{C}_{i,t-1}}$) is positive and significant. Comparing the estimated effect of β_2 (Table 9) with the estimation of β_2 in prediction 1 (Table 8 model 4) it can be seen that the coefficients are almost the same. For the second prediction β_2 is estimated at around 0.14 meaning that workers who move again within the same region almost completely reverse the original impact of $\bar{C}_{i,t-1}$ (which was estimated by 0.16 in the previous analysis –Table 8 model 4).

Table 9: Adjustment of the commuting time in t+1

NUTS-3 region	Dependent variable: ln($C_{i,t+1} - C_{i,t=0}$)
$\mathbf{ln}(\boldsymbol{\bar{C}_{i,t=0} - \bar{C}_{i,t-1}})$	0.140*
	(0.080)
Change in ln(wage)	-0.047
	(0.069)
Inverse of Mill´s ratio*	1.819***
	(0.039)
Constant	-2.513***
	(0.049)
N	3,988
R^2	0.363
Adj. R^2	0.363

Notes: The table reports the regression of the adjustment of the individually selected commuting time after the second movement on the difference between the average commutes of the new and the old region. Standard errors clustered by nuts3 regions, below parameter estimates. Level of significance: *1%, **5%, ***10%.

*Inverse of Mill´s ratio is obtained from the first stage probit estimation of moving again within the new region.

Source: Own calculation based on BeH V10.01.00.

With this result, I can therefore exclude an explanation for the commuting behaviour, which is based on stable unobserved differences across movers from different region. As individuals readjust their commuting time by moving again within the new region – they adapt the commuting behaviour of the new region.

4.3 Robustness checks

Although the presence of stable unobserved differences can be excluded with the proof of prediction 2, there could be other explanations for the presented results and several issues that might influence the output, like unobserved heterogeneity and sorting. However, in the following, I cannot only reject other explanations, but I can also confirm my results with serval robustness checks. Therefore, the effect of $\bar{C}_{i,t-1}$ on $C_{i,t=0}$ can be interpreted as causal.

Unobserved heterogeneity

In fact, unobserved heterogeneity can have an influence on the estimates of $\bar{C}_{i,t-1}$ and thus driving the effect of the context (see chapter 3.2). Dealing with this issue, I exclude all observable individual and firm characteristics in my analysis.

Table 10: Robustness check: Individually selected commuting time after the movement

NUTS-3 region	Dependent variable: Log($C_{i,t=0}$)
Log ($\bar{C}_{i,t=0}$)	0.577***
	(0.076)
Log($\bar{C}_{i,t-1}$)	**0.118****
	(0.059)
Log($C_{i,t-1}$)	0.048**
	(0.022)
Log($C_{i,t-2}$)	0.049**
	(0.023)
Working place type	Yes
Living place type	Yes
Constant	0.533**
	(0.217)
N	14,745
R^2	0.040
Adj. R^2	0.039

Notes: This table reports the regression of the individually selected log commuting time after the first relocation on the average log commuting time of the region before the movement, without any observable individual and firm characteristics. Standard errors clustered by NUTS-3 regions, below parameter estimates. Levels of significance: *1%, **5%, ***10%.

Source: Own calculation based on BeH V10.01.00.

The results show that the influence of past-observed commuting options is still positive and significant. Moreover, comparing $\bar{C}_{i,t-1}$ with the effect of Table 8 (model 4) – with the inclusion of all control variables – the coefficient reduces by about 27 percent (from 0.161 to 0.118). Thus, observable individual characteristics change the influence of the context only in small dimension. By assuming that unobservable characteristics also have the same small effect, this leaves only little room for the issue of unobserved heterogeneity.

Sorting

Moreover, also sorting can be a problem, as workers select themselves in certain regions because of their taste for commuting. To face this issue I run the reversed regression of equation 3. In line with the sorting issue I should find a positive correlation between the average commuting time of the destination region and the own drive time of the region before the movement. However, my results show no significant effect of the mean commuting time in the destination regions (see Appendix C). Thus, there is no sign of a sorting process – individuals do not select themselves in regions because of their taste for commuting – but it once again shows the presence of the context effect.

Moreover, workers also might move for job related reasons, like higher wages. As wages are after theory high correlated with commuting, I consider only workers who have almost the same wage before and after the first movement. Appendix D reports the results. They show that the average commuting time of the region before the movement has a positive and significant influence on the commuting time of workers who do not experience an increase in wages after the relocation. This indicates that endogeneity issues with respect to wages do not drive the results.

Due to the exclusion of the issues of unobserved heterogeneity sorting and endogeneity, the influence of the context of past observed-commutes on the individually chosen commuting time can be interpreted as causal.

In the following, to get a deeper look inside the drivers of the context effect, I do robustness checks in which I consider movers between different types of regions as well as movers between municipalities and labour market regions. Moreover, I consider movers who change their place of residence, holding workplace location constant and I differentiate movers by age groups and gender.

Rural vs urban areas

In the following, I consider movers between different residence place types, like rural and urban areas. Appendix E shows the results and indicates that the context of past-observed commuting options has a positive and significant effect for movers between two urban areas. This is close to Simonsohn´s (2006) findings, since he considers movers between two metropolitan areas in the US. In addition, past-observed commutes influence the commuting decisions of workers who relocate from rural to urban areas. In particular, workers living in previous rural regions with high average commutes are used to commute long ways. Therefore, when moving to urban regions workers have a higher tolerance for commuting and choose higher commutes than the average. However, if employees move to rural areas regardless of whether they come from rural or urban regions, the context of past-observed commutes seems not to play a role for commuting decisions. The coefficients are both insignificant. The reason might be that especially in rural areas other conditions, such as the availability of jobs are more important than commuting preferences.

Municipalities and labour market regions

Next, I demonstrate that the results are also valid for movers between German municipalities. The restrictions are the same as for movers between NUTS-3 regions, i.e. workers have to change their working and residence place between 11,190 municipalities. Moreover, their municipality of working and residence place has to be constant for two years before and after the movement. In contrast, to the consideration of movers between NUTS-3 regions, I calculate the average commuting time on the municipality level (as a proxy for past-observed commuting options).

The results show as well the presence of the context effect (see Appendix F): The mean commuting time of the previous community has a positive significant influence on the individual chosen commuting time in the region after the movement. Although this effect is smaller, it still remains significant when including the individual drive time of the previous municipality (model 3) and omitting daily wages (model 5).

However, considering labour market regions, I find no effect of the context, as the average commuting time of the previous labour market region is insignificant (see Appendix G). This could be related to the fact that past-observed commuting options influence only workers who relocate from rural to urban areas as well as between two urban regions. As labour market region include urban and rural areas, this makes labour market regions more heterogeneous. However, this heterogeneity cannot be offset, by taking average commuting times for an entire labour market region. Consequently, including rural as well as urban areas, the effects could be cancelled out.

Movers only change their place of residence

Considering workers who only change residence place holding workplace location constant I find no effect of the context of past-observed commutes (see Appendix H). The average commuting time of the region before the movement has no significant effect on the individually selected commuting time after the movement. The reason could be that movers are relocating for reasons related to commuting: Workers who are dissatisfied with their commuting time may look for a living place closer to their place of work. This could explain why the context of past-observed commutes in the region before the movement has no effect on the commuting behaviour for this kind of movers.

If workers however change both place of residence and work when moving the context of past-observed commutes has a positive effect on the individually selected commuting time in the destination region. This could be related to the fact that one of the major reasons for this kind of relocation is job related.

Age groups

Since it is possible that individuals differ in their behaviour due to their age, I take up this point by making the estimation for different age groups. The results, which are provided in Appendix I, indicate that past-observed commuting options have the highest effect on workers who are between 45 and 56 years old. This could be related to the fact that older workers have lived in regions for a longer period before the movement. Therefore, the context may have a greater influence on the chosen commuting time after the relocation. However, since I have no information about the place of residence before 2000, I cannot confirm this hypothesis.

In addition, there is evidence of the context effect for the both youngest groups. Nevertheless, for the group of workers, who are between 35 and 44 the context of past-observed commuting options has no significant effect.

Men and women

Considering men and women separately shows no difference between the effect of the context of observed commutes for men and women (see Appendix J). Although men and women commute differently, as women travel less than men to work the context of past observed commutes has almost the same effect for both.

5 Discussion

According to the theory of the Background Context Effect, I show that workers current commuting behaviour is influenced by past-observed options. Employees who have experienced higher commutes in the past are more likely to choose longer commutes when moving to a new region compared to workers who have experienced less commutes.

However, the commuting behaviour in the new region can also result due to endogeneity resulting from a reverse causality between wages and commuting, selectivity issues or unobserved heterogeneity. For this reason, I did several robustness checks showing that my results are not driven by such problems.

Another neglected effect could be caused by imperfect information: Moving to a new region workers don´t know about the commuting situation in the new region. Therefore, they might commute longer in the beginning and then change their commutes by relocating again within the new region – explaining the second prediction. However, information about commuting and the local housing market is relatively low. Nevertheless, what is high are the cost of commuting: It takes time, causes stress and is very expansive. Therefore, I would expect that workers inform themselves before the movement about the commuting condition in the new region.

Moreover, as I only consider commuting distances and times, which are calculated based on the use of a car, I exclude the fact that workers use public transport. However, most of the German employees, almost 70 percent, use the car to travel to work. Whereas only 14 percent of commuters use the public transport system. Moreover, the results from Simonsohn (2006) show that the context has almost the same effect for people who use public transport.

6 Conclusion

This study investigates for the first time the commuting behaviour in terms of a behavioural economic concept based on geo-referenced data for Germany. The basis of this investigation is the approach of Simonsohn (2006), who examines the commuting behaviour for the US. Like him, I can show that workers commuting decisions are influenced by past-observed commuting options. This explains why individuals who move from different regions into the same region commute differently at the beginning: Persons coming from areas with high average commutes have a higher tolerance for commuting and therefore commute more than individuals coming from previous regions with shorter commutes. However, when staying in the new region, they adjust their initial chosen commuting times to the average commutes in the new region. This refutes the assumption of stable unobserved differences across individuals. Instead, individuals change their marginal utility of commuting if moving to a new region, as they adjust their commuting time by a second relocation within the new region. The reason for this behaviour is the change of the context: The original context was seen as the average commuting time of the previous region, but with the relocation to a new region the context changes. Thus, commuting preferences change. For this reason, future studies, which investigate consumer preference, should also try to identify the context of previous observed options and include them in their analysis.

Since I can distinguish between different residence types, like rural and urban areas, compared to Simonsohn (2006), I can show that past-observed commuting options only affect the commuting decision of workers moving to urban areas. The commuting decisions of employees who relocate to rural areas are instead not affected by the context – other factors, such as the availability of jobs, are more important. For movers who only change their place of residence (holding workplace location constant) I also find no effect by the context of past-observed commutes. This can be caused by the fact that workers change their place of living for reasons, which are related to the dissatisfaction regarding commuting. Estimating the context effect for different age groups shows that this effect is strongest for older employees. In addition, I can confirm my results for both movers between German NUTS-3 regions and municipalities. My robustness-checks show that these results are also stable for unobserved heterogeneity, selectivity and endogeneity issues.

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Appendix

Appendix A: Descriptive statistics of movers: Different types of residence place and workplace

Variable	Percent
Residence place type	
Metropolitan city	38.83
Δ Metropolitan city	+2.95
City	28.30
Δ City	-1.86
Large town	14.00
Δ Large town	+0.13
Small town	11.01
Δ Small town	-0.53
Rural area	7.87
Δ Rural area	-0.70
Working place type	
Metropolitan city	46.11
Δ Metropolitan city	+3.83
City	30.27
Δ City	-1.96
Large town	11.73
Δ Large town	-0.42
Small town	7.82
Δ Small town	-0.91
Rural area	4.07
Δ Rural area	-0.54
N	14,745

Note: Proportions of different types of residence place and workplace. Comparison before and after the movement.
Source: Own calculation based on BeH.

Appendix B: Probit regression whether workers move for a second time

NUTS-3 region	Workers moves for a second time
Log ($\bar{C}_{i,t=0}$)	0.284**
	-0.137
Age groups	Yes
Log (wage)	-0.029
	-0.037
Woman	-0.074**
	-0.029
High skilled	-0.271***
	-0.054
Medium skilled	-0.085**
	-0.043
Occupation dummies	Yes
Industry dummies	Yes
Occupational status	Yes
Dummy migrant	0.132**
	-0.064
Supervisor	-0.042
	-0.087
Leading position	0.092
	-0.116
Specialist/expert	0.021
	-0.071
Trained/professional assistant	-0.003
	-0.064
Firm size (Number of workers)	Yes
Year Dummies	Yes
Residence place type	Yes
Working place type	Yes
West	0.134**
	-0.053
Log($\boldsymbol{C}_{i,t=0} - \bar{\boldsymbol{C}}_{i,t=0}$)	0.540***
	(0.019)
Constant	-0.956**
	-0.479
N	14,745

Notes: The table reports the results of the probit regression, whether a worker moves for a second time (first step of the Heckman selection model). Standard errors clustered by NUTS-3 regions, below parameter estimates. Levels of significance: *1%, **5%, ***10%.

Source: Own calculation based on BeH.

Appendix C: Robustness check: Individuals sort themselves in regions because of their taste for commuting.

NUTS-3 region	Dependent variable Log($C_{i,t-1}$)
Log ($\bar{C}_{i,t=0}$)	-0.111
	(0.081)
Age groups	Yes
Log (wage)	0.088***
	(0.019)
Woman	-0.063***
	(0.018)
HQ	0.077**
	(0.034)
MQ	0.057**
	(0.027)
Occupation	Yes
Industry	Yes
Occupational status	Yes
Dummy migrant	-0.039
	(0.035)
Supervisor	-0.012
	-0.052
Leading position	0.006
	-0.076
Specialist/expert	0.005
	-0.042
Trained/professional assistant	-0.043
	-0.039
Firm size (Number of workers)	Yes
Year Dummies	Yes
Residence place type	Yes
Working place type	Yes
West	0.021
	(0.035)
Log($C_{i,t=0}$)	0.080***
	(0.009)
Log($\bar{C}_{i,t-1}$)	0.948***
	(0.060)
Constant	-0.552
	(0.347)
N	14,745
R^2	0.057
Adj. R^2	0.054

Notes: The table reports the regression of the individual commuting time in the previous region on the average commuting time in the target region (after the movement). Standard errors clustered by NUTS-3 regions, below parameter estimates. Levels of significance: *1%, **5%, ***10%.

Source: Own calculation based on BeH.

Appendix D: Robustness check: Movers, who have almost the same wage before and after the movement.

NUTS-3 region	Dependent variable Log($C_{i,t=0}$)
Log ($\bar{C}_{i,t=0}$)	0.408***
	-0.112
Age groups	Yes
Woman	-0.079**
	-0.039
HQ	-0.056
	-0.081
MQ	-0.037
	-0.061
Occupation	Yes
Industry	Yes
Occupational status	Yes
Dummy migrant	0.055
	-0.076
Supervisor	0.104
	-0.124
Leading position	-0.146
	-0.201
Specialist/expert	0.03
	-0.084
Trained/professional assistant	0.053
	-0.076
Firm size (Number of workers)	Yes
Year Dummies	Yes
Residence place type	Yes
Working place type	Yes
West	0.013
	-0.042
Log($\boldsymbol{\bar{C}_{i,t-1}}$)	0.242**
	-0.104
Log($C_{i,t-1}$)	0.088***
	-0.019
Constant	0.593
	-0.455
N	2,972
R^2	0.072
Adj. R^2	0.051

Notes: The table reports the regression of the individually selected commuting time the first relocation on the average log commuting time of the region before the movement and control variables, for workers who have almost the same wage before and after the movement. Standard errors clustered by NUTS-3 regions, below parameter estimates. Levels of significance: *1%, **5%, ***10%.

Source: Own calculation based on BeH.

Appendix E: Robustness check: Relocation between different types of regions.

NUTS-3 region	Dependent variable: Log($C_{i,t=0}$)			
	Rural to urban	**Rural to rural**	**Urban to rural**	**Urban to urban**
Log ($\bar{C}_{i,t=0}$)	0.463***	0.328***	0.536***	0.873***
	(0.109)	(0.117)	(0.120)	(0.115)
Log (wage)	0.097*	0.134**	0.090*	0.037
	-0.055	-0.059	-0.049	-0.033
Woman	-0.012	0.068	-0.061	-0.033
	-0.041	-0.044	-0.038	-0.025
HQ	0.054	0.001	-0.019	-0.133***
	-0.08	-0.1	-0.082	-0.045
MQ	0.034	0.061	0.02	-0.085**
	-0.06	-0.079	-0.073	-0.04
Occupation	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Occupational status	Yes	Yes	Yes	Yes
Dummy migrant	-0.024	-0.038	-0.007	-0.054
	-0.088	-0.126	-0.087	-0.05
Supervisor	-0.186	0.039	0.118	-0.041
	-0.132	-0.123	-0.118	-0.062
Leading position	-0.126	-0.105	-0.1	-0.009
	-0.177	-0.288	-0.139	-0.092
Specialist/expert	0.029	0.176*	0.136	-0.051
	-0.093	-0.106	-0.094	-0.064
Trained/professional assis-tant	0.095	0.014	0.139	-0.047
	-0.079	-0.089	-0.085	-0.061
Firm size (Number of work-ers)	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Residence place type	Yes	Yes	Yes	Yes
Working place type	Yes	Yes	Yes	Yes
West	0.01	-0.143**	-0.116**	0.113***
	-0.045	-0.059	-0.052	-0.041
Log($\bar{\boldsymbol{C}}_{\boldsymbol{i,t-1}}$)	0.402***	0.052	-0.102	0.163**
	-0.131	-0.138	-0.108	-0.072
Log($C_{i,t-1}$)	0.054***	0.048**	0.033*	0.094***
	-0.02	-0.023	-0.018	-0.012
Constant	-0.735	1.370**	1.371**	-0.531
	-0.883	-0.56	-0.536	-0.486
N	2,951	1,919	2,767	7,108
R^2	0.072	0.158	0.139	0.074
Adj. R^2	0.052	0.129	0.118	0.065

Notes: The table reports regressions of the individually selected log commuting time after the first relocation on the average log commuting time of the region before the movement and control variables, for different regional types. Standard errors clustered by NUTS-3 regions, below parameter estimates. Levels of significance: *1%, **5%, ***10%.

Source: Own calculation based on BeH.

Appendix F: Robustness check: Relocation between German municipalities

Municipality level	**Dependent variable: Log($C_{i,t=0}$)**				
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Log ($\bar{C}_{i,t=0}$)	0.752***	0.695***	0.702***	0.701***	0.706***
	-0.043	-0.047	-0.046	-0.046	-0.046
Age groups	Yes	Yes	Yes	Yes	Yes
Log (wage)	0.078***	0.080***	0.073***	0.073***	
	-0.023	-0.022	-0.022	-0.022	
Woman	-0.051***	-0.050***	-0.044**	-0.044**	-0.057***
	-0.017	-0.017	-0.017	-0.017	-0.017
HQ	-0.050*	-0.047	-0.050*	-0.051*	-0.032
	-0.029	-0.029	-0.029	-0.029	-0.028
MQ	-0.022	-0.023	-0.024	-0.024	-0.022
	-0.024	-0.024	-0.024	-0.024	-0.024
Occupation	Yes	Yes	Yes	Yes	
Industry	Yes	Yes	Yes	Yes	
Occupational status	Yes	Yes	Yes	Yes	Yes
Dummy migrant	-0.054	-0.048	-0.048	-0.048	-0.05
	-0.038	-0.038	-0.037	-0.037	-0.037
Supervisor	-0.064	-0.062	-0.061	-0.061	-0.056
	-0.045	-0.045	-0.045	-0.045	-0.044
Leading position	-0.061	-0.059	-0.058	-0.058	-0.043
	-0.067	-0.066	-0.066	-0.066	-0.066
Specialist/expert	0.058	0.062*	0.060*	0.060*	0.076**
	-0.036	-0.036	-0.036	-0.036	-0.036
Trained/professional assistant	0.033	0.036	0.038	0.038	0.05
	-0.031	-0.031	-0.031	-0.031	-0.031
Firm size (Number of workers)	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Residence place type	Yes	Yes	Yes	Yes	Yes
Working place type	Yes	Yes	Yes	Yes	Yes
West	0.016	0.017	0.016	0.017	0.029
	-0.042	-0.04	-0.039	-0.038	-0.036
Log($\bar{\boldsymbol{C}}_{\boldsymbol{i,t-1}}$)		0.182***	0.098**	0.098**	0.095**
		-0.042	-0.044	-0.044	-0.044
Log($C_{i,t-1}$)			0.076***	0.063***	0.063***
			-0.008	-0.023	-0.023
Log($C_{i,t-2}$)				0.014	0.015
				-0.023	-0.023
Constant	0.092	-0.332	-0.311	-0.311	-0.143
	-0.331	-0.322	-0.321	-0.321	-0.32
N	17,506	17,506	17,506	17,506	17,506
R^2	0.069	0.071	0.076	0.076	0.075
Adj. R^2	0.062	0.067	0.072	0.072	0.072

Notes: The table reports regressions of the individually selected log commuting time after the first relocation on the average log commuting time of the region before the movement and control variables, on municipality levels. Standard errors clustered by municipalities regions, below parameter estimates. Levels of significance: *1%, **5%, ***10%.

Source: Own calculation based on BeH.

Appendix G: Robustness check: Relocation between German labour market regions.

Labor market region level	Dependent variable: $\text{Log}(C_{i,t=0})$				
	Model 1	Model 2	Model 3	Model 4	Model 5
Log ($\bar{C}_{i,t=0}$)	0.578***	0.579***	0.588***	0.586***	0.589***
	-0.101	-0.104	-0.103	-0.103	-0.102
Age groups	Yes	Yes	Yes	Yes	Yes
Log (wage)	0.071***	0.071***	0.066**	0.066**	
	-0.027	-0.027	-0.027	-0.027	
Woman	0.002	0.002	0.006	0.006	-0.005
	-0.021	-0.021	-0.021	-0.021	-0.021
HQ	-0.070*	-0.070*	-0.075**	-0.075**	-0.059*
	-0.036	-0.036	-0.036	-0.036	-0.034
MQ	-0.026	-0.026	-0.031	-0.031	-0.03
	-0.036	-0.036	-0.036	-0.036	-0.036
Occupation	Yes	Yes	Yes	Yes	
Industry	Yes	Yes	Yes	Yes	
Occupational status	Yes	Yes	Yes	Yes	
Dummy migrant	-0.054*	-0.054*	-0.05	-0.05	-0.052
	-0.032	-0.032	-0.032	-0.032	-0.031
Supervisor	-0.044	-0.044	-0.041	-0.041	-0.036
	-0.054	-0.054	-0.053	-0.053	-0.053
Leading position	-0.007	-0.007	-0.004	-0.003	0.01
	-0.073	-0.073	-0.071	-0.071	-0.072
Specialist/expert	0.045	0.045	0.045	0.047	0.061
	-0.047	-0.047	-0.047	-0.047	-0.047
Trained/professional assistant	0.023	0.023	0.025	0.027	0.037
	-0.041	-0.041	-0.041	-0.041	-0.041
Firm size (Number of workers)	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Residence place type	Yes	Yes	Yes	Yes	Yes
Working place type	Yes	Yes	Yes	Yes	Yes
West	0.014	0.014	0.013	0.012	0.023
	-0.024	-0.025	-0.024	-0.024	-0.024
$\text{Log}(\bar{C}_{i,t-1})$		-0.006	-0.065	-0.068	-0.065
		-0.126	-0.129	-0.13	-0.129
$\text{Log}(C_{i,t-1})$			0.063***	0.035*	0.035*
			-0.01	-0.019	-0.019
$\text{Log}(C_{i,t-2})$				0.032*	0.033*
				-0.018	-0.018
Constant	0.566	0.58	0.586	0.584	0.733
	-0.377	-0.443	-0.446	-0.446	-0.451
N	12,239	12,239	12,239	12,239	12,239
R^2	0.042	0.042	0.0456	0.046	0.045
Adj. R^2	0.037	0.037	0.041	0.041	0.041

Notes: The table reports regressions of the individually selected log commuting time after the first relocation on the average log commuting time of the region before the movement and control variables, for labor market regions. Standard errors clustered by labor market regions, below parameter estimates. Levels of significance: *1%, **5%, ***10%.

Source: Own calculation based on BeH.

Appendix H:Robustness check: Movers only change their place of residence (workplace location is kept constant).

NUTS-3 region	Dependent variable Log($C_{i,t-1}$)
Log ($\bar{C}_{i,t=0}$)	0.483***
	-0.029
Log (wage)	0.040***
	-0.007
Age groups	Yes
Woman	-0.014***
	-0.005
HQ	0.005
	-0.008
MQ	-0.001
	-0.006
Occupation	Yes
Industry	Yes
Occupational status	Yes
Dummy migrant	-0.035***
	-0.009
Supervisor	-0.01
	-0.015
Leading position	-0.005
	-0.027
Specialist/expert	0.033***
	-0.011
Trained/professional assistant	0.011
	-0.009
Firm size (Number of workers)	Yes
Year Dummies	Yes
Residence place type	Yes
Working place type	Yes
West	-0.012
	-0.008
Log($\boldsymbol{\bar{C}_{i,t-1}}$)	0.023
	-0.022
Log($C_{i,t-1}$)	0.466***
	-0.006
Constant	-0.182**
	-0.091
N	150,600
R^2	0.253
Adj. R^2	0.253

Notes: The table reports regressions of the individually selected log commuting time after the first relocation on the average log commuting time of the region before the movement and control variables. Movers only change their residence place workplace location stays constant. Standard errors clustered by NUTS-3 regions, below parameter estimates. Levels of significance: *1%, **5%, ***10%.

Source: Own calculation based on BeH.

Appendix I: Robustness check: Individually selected commuting time after the movement for different age groups.

NUTS-3 region	Dependent variable: Log($C_{i,t=0}$)			
Age groups	18-24	25-34	35-44	45-56
Log ($\bar{C}_{i,t=0}$)	0.592***	0.611***	0.525***	0.649***
	-0.136	-0.097	-0.116	-0.166
Log (wage)	0.125	0.025	0.080**	0.085
	-0.076	-0.03	-0.04	-0.061
Woman	0.008	-0.032	-0.033	-0.049
	-0.046	-0.025	-0.033	-0.059
HQ	-0.250**	-0.127***	-0.042	0.242*
	-0.107	-0.044	-0.074	-0.123
MQ	-0.012	-0.087**	-0.009	0.166
	-0.056	-0.043	-0.065	-0.116
Occupation	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Occupational status	Yes	Yes	Yes	Yes
Dummy migrant	0.029	-0.079	-0.042	0.034
	-0.115	-0.051	-0.068	-0.14
Supervisor	0.191	-0.099	-0.01	-0.067
	-0.213	-0.064	-0.082	-0.161
Leading position	0.611***	0.054	-0.126	-0.524***
	-0.215	-0.112	-0.106	-0.202
Specialist/expert	0.085	0.027	0.097	-0.031
	-0.104	-0.069	-0.088	-0.123
Trained/professional assistant	-0.022	0.049	0.095	-0.048
	-0.083	-0.066	-0.081	-0.106
Firm size (Number of workers)	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Residence place type	Yes	Yes	Yes	Yes
Working place type	Yes	Yes	Yes	Yes
West	-0.088	0.033	0.013	0.048
	-0.057	-0.045	-0.066	-0.069
Log($\bar{\boldsymbol{C}}_{\boldsymbol{i,t-1}}$)	0.297***	0.138*	0.043	0.315**
	-0.113	-0.091	-0.09	-0.141
Log($C_{i,t-1}$)	0.035*	0.073***	0.109***	0.103***
	-0.02	-0.012	-0.017	-0.027
Constant	0.322	0.46	-0.088	-0.987
	-0.523	-0.405	-0.69	-1.101
N	2,245	7,070	3,885	1,545
R^2	0.082	0.056	0.068	0.109
Adj. R^2	0.055	0.047	0.052	0.070

Notes: The table reports regressions of the individually selected log commuting time after the first relocation on the average log commuting time of the region before the movement and control variables, for different age groups. Standard errors clustered by NUTS-3 regions, below parameter estimates. Levels of significance: *1%, **5%, ***10%.

Source: Own calculation based on BeH.

Appendix J: Robustness check: Individually selected commuting time after the movement for women and men.

NUTS-3 region	Dependent variable: Log($C_{i,t=0}$)	
	Women	Men
Log ($\bar{C}_{i,t=0}$)	0.573***	0.604***
	-0.082	-0.099
Log (wage)	0.060*	0.067**
	-0.034	-0.031
Woman	0.008	-0.032
	-0.046	-0.025
HQ	-0.087*	-0.057
	-0.047	-0.05
MQ	-0.075*	0.011
	-0.044	-0.042
Occupation	Yes	Yes
Industry	Yes	Yes
Occupational status	Yes	Yes
Dummy migrant	-0.037	-0.046
	-0.058	-0.048
Supervisor	-0.005	-0.063
	-0.094	-0.06
Leading position	-0.065	-0.078
	-0.127	-0.084
Specialist/expert	0.011	0.073
	-0.066	-0.06
Trained/professional assistant	-0.006	0.069
	-0.059	-0.055
Firm size (Number of workers)	Yes	Yes
Year Dummies	Yes	Yes
Residence place type	Yes	Yes
Working place type	Yes	Yes
West	0.007	0.024
	-0.029	-0.065
Log($\bar{\boldsymbol{C}}_{\boldsymbol{i,t-1}}$)	0.185***	0.150*
	-0.071	-0.077
Log($C_{i,t-1}$)	0.058***	0.098***
	-0.012	-0.012
Constant	0.551	-0.687
	-0.339	-0.482
N	7,276	7,469
R^2	0.062	0.059
Adj. R^2	0.053	0.050

Notes: The table reports regressions of the individually selected log commuting time after the first relocation on the average log commuting time of the region before the movement and control variables, for women and men. Standard errors clustered by NUTS-3 regions, below parameter estimates. Levels of significance: *1%, **5%, ***10%.

Source: Own calculation based on BeH.

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