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Abstract:

Being at the heart of today's working life, commuting is of central interest to geographers, policy makers, transport planners and economists alike. This article analyzes aggregate commuting using various groups of variables. A special focus is on the questions whether and how the provision of local public goods, such as educational institutions or health care facilities, and local amenities affect commuting decisions on the aggregate level and to what extent commuting can be explained by labor market characteristics at the source and target units. The empirical investigation analyzes aggregate commuting flows between municipalities of an Austrian province using censored regression and count data models.

Key words: commuting, gravity model, censored regression

JEL classifications: R23, C24, C25

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1. Introduction

Commuting is an important phenomenon of today's working life: according to OECD (2005) figures, interregional commuting rates[1] are as high as 16 % of resident employment in Germany and the United Kingdom, and higher than 10 % for countries like France, the Netherlands and Italy. Accordingly, intraregional commuting, e.g. at the municipality level, is even higher.

Commuting has one obvious drawback: it is costly to the individual, both in terms of money and in terms of time. But it can also have positive side effects: the spatial separation of residence and workplace locations allows workers to reside off urban areas where land prices are lower and/or environmental living conditions are better while working where labor market conditions are more promising. In addition, commuting trips need not only serve the single purpose of getting to work: workers can enjoy shopping possibilities at the target or consume local amenities their residence location does not offer, including a larger variety of public goods. The choice of workplace and residence locations can be made in order to choose the best of two worlds: living where the highest place utility can be derived from, working where the best labor market conditions prevail, and choosing where to enjoy consumer amenities and/or local public goods.

The importance of local amenities and local public goods for the choice of the residence location is a well-researched topic since the seminal paper by Tiebout (1956), and has been emphasized by Friedman (1981), Knapp and Graves (1989), Nechyba and Strauss (1998), Hunt and Mueller (2004), Bayoh, Irwin and Haab (2006), Okamoto (2007), or in a recent paper by Krupka (2009), to name just a few. But spatial differences in the provision of local public goods can also affect commuting: at the target municipality, the provision of local public goods can constitute an auxiliary utility of a commuting trip, thereby increasing in-commuting. Furthermore, consumer amenities such as shopping possibilities can also exert a positive effect on commuting. It can thus be assumed that individuals choose a workplace locations which offers public goods or amenities their residence location does not have or where a larger variety of these public goods or amenities can be found. Furthermore, if public goods are public capital goods rather than public consumption goods and constitute a factor of production (like investments in infrastructure), they can increase the returns-to-scale in an area which benefits not only residents but also commuters via higher wages (Guo, 2009).

[1] The term "regions" refers to the provincial level, mainly NUTS-2 regions.

However, only few articles explored the connection between commuting and public goods theoretically (see, for example, Sasaki, 1991), while there are virtually no papers analyzing the influence of spatial differences in the provision of local public goods on commuting empirically. One notable exception is the paper by Merriman and Hellerstein (1994), who use the number of parks per 100 km² to measure public amenities at the commuting target in their study on commuting in the Tokyo metropolitan area but unexpectedly find a negative effect on commuting.

This paper extends previous studies on the determinants of aggregate commuting flows (e.g., Glejser and Dramais, 1969, Congdon, 1983, Thorsen and Gitlesen, 1998, Merriman and Hellerstein, 1994, Renkow, 2003, to name just a few) by exploring the influence of the level or variety of consumer amenities and local public goods on the choice of commuting targets at the aggregate level in an empirical place-to-place model of commuting, taking the residence location as given. The underlying hypothesis is that the provision of local public goods at the target municipality can be the source of an auxiliary utility of a commuting trip, thereby increasing in-commuting to a municipality which is well-equipped with local public goods (after controlling for the level of public goods in the residence municipality). The same argument applies to consumer amenities such as shopping possibilities in the target municipality.

The econometric approach follows a "gravity model" specification where the "gravitational force" (the flow of commuters) between two units depends on the distance between them as well as on the "mass" (population) of the units. The gravity model has a long tradition in economic research since it was introduced to international economics by Tinbergen (1962) and Pöyhönen (1963) in order to explain differences in the cross-country variation of trade flows (although earlier applications of models resembling the Newtonian relationship were common in other fields of science, see Isard, 1960, or Sen and Smith, 1995). Despite being a deterministic relationship which initially lacked theoretical foundations[2], the gravity model continues to be a popular tool among economists aimed at explaining flow variables mainly due to its impressive performance in empirical applications. E.g., Leamer and Levinsohn (1995, p. 1384) count empirical applications of the gravity model among "the clearest and most robust empirical findings in economics". The model is thus applied not only in international economics (see Linneman, 1966, Havrylyshyn and Pritchett, 1991, Eichengreen and Irwin, 1995, 1998, Deardorff, 1998, Anderson and Smith,

[2] See, e.g., Deardorff (1998) for a discussion of the criticism concerning the use of the gravity equation in international economics and approaches to derive the gravity model from standard trade theory.

1999, Egger, 2000, Soloaga and Winters, 2001, Porojan, 2001, Anderson and van Wincoop, 2003, Santos Silva and Tenreyro, 2006, to name just a few), but also in other fields such as migration research (see Greenwood, 1997, for an overview or Karemera, Oguledo and Davis, 2000, Pedersen, Pytlikova and Smith, 2004, Clark, Hatton and Williamson, 2008, Ortega and Peri, 2009, for some recent contributions). Gravity models are also used to estimate flows of commuters (see Glejser and Dramais, 1969, Thorsen and Gitlesen, 1998, Renkow and Hoover, 2000, Shields and Swensson, 2000, Renkow, 2003, Johansson, Klaesson and Olsson, 2003, etc.).

The empirical application uses a unique set of census data with information on place-to-place commuting flows between municipalities in the Austrian province of Vorarlberg. Because some residence-workplace combinations were not chosen by individuals (e.g., because they are not attractive enough compared to alternative combinations) and therefore no commuting is observed for a range of municipality pairs, suitable censored regression models must be used to estimate the parameters of interest. Otherwise, excluding the information contained in the "zero observations" (where the flow variable has a value of zero) introduces a truncated sample, which generally leads to biased and inconsistent estimates of the parameters. The literature provides several approaches to estimate gravity models when the dependent variable has zero values, especially in the literature on international trade flows (for an overview see Frankel, 1997): among the most widely used alternative models are Tobit (e.g., Havrylyshyn and Pritchett, 1991, Eichengreen, 1995, Soloaga and Winters, 2001) or scaled OLS (e.g., Eichengreen and Irwin, 1995, 1998). These models are also used in studies on migration (see, for example, Ortega and Peri, 2009). An application of the Tobit model to commuting flows can, e.g., be found in Shields and Swenson (2000).

Most of the international trade literature, however, ignores the problem of zero observations (Santos Silva and Tenreyro, 2006, p. 643) because inference from flow estimations hardly changes whether zero observations are considered or not.[3] The main reason for this finding is that the proportion of zero observations in trade data is rather small (at least at high levels of aggregation) and mostly relates to long-distance relationships. Because the sample used in this paper includes a large proportion of municipality pairs for which no commuting is observed, application of suitable censored regression models is, however, of great importance. The empirical analysis

[3] E.g., Soloaga and Winters (2001) note that "[…] the appropriate estimation procedure is strictly a Tobit model, and we follow this approach in the paper. In truth, however, this refinement does not add much relative to the more normal OLS estimation" (p. 7).

shows that there are large differences in the estimated parameters depending on whether these observations enter the econometric model or not, and that considering zero observations significantly improves estimation of commuting flows.

A second family of econometric approaches used in the literature is count data models (see Santos Silva and Tenreyro, 2006, and Mathä and Wintr, 2009, for recent applications). While linear and censored regression models treat the dependent variable as continuous, these models take into account the nature of the regressand (a flow of individuals) as being a strictly non-zero integer. Both the Poisson as well as the negative binomial regression models will thus be applied to the data, as well as zero-inflated models.

The structure of this paper is as follows: section 2 introduces a simple framework for aggregate commuting. Section 3 presents the data and hypotheses about possible determinants of the aggregate commuting flows. Next, section 4 describes the empirical models used. Estimation results from the linear, censored and count data models are presented and discussed in section 5. Section 6 concludes.

2. A framework for aggregate commuting

This section introduces a basic view of how the decisions of utility-maximizing individuals are aggregated into a commuting flow and serves as a framework to think about regional commuting. The framework assumes that if individuals can freely choose their place of work and if they have perfect information, they will choose the municipality which provides them with the highest utility, given their place of residence. An alternative view of the individual's decision could be based on a search model: the individual receives job and residence offers from a specific distribution and then chooses whether to accept the offer or not. In this case, a "snapshot" of the equilibrium in the search model is observed, where all individuals are in their present optimum based on the job and residence offers they received up to now. For a theoretical view on job search theory in the context of commuting decisions see, for example, Rouwendal (2004) or van Ommeren, Rietveld and Nijkamp (1997, 1999, 2000).

Assuming that the region consists of $i = 1, \dots, I$ units and that the choice of residence location is predetermined, individuals only have to choose their workplace location. An individual h derives his utility from a set of characteristics of the regional unit $j \in I$ she works in, m_j, including job and labor market characteristics, local amenities, and local public goods. The individual compares these characteristics m_j to those of its unit of residence, m_i. It can be assumed that if the target unit is "better equipped" with preferable characteristics (or has characteristics the source unit does not share), the higher the utility from commuting to the target unit j. The utility of an individual h living in regional unit i and working in another regional unit j is then given by $u_{hji}(m_i, m_j, d_{ji})$ with d_{ji} being the costs of commuting from i to j[4]: the utility is increasing in m_i and m_j and decreasing in d_{ji}.

Since the individual only chooses where to work it will commute to a regional unit j if the utility of working in j exceeds the utility of working "at home", $u_{hji}(m_i, m_j, d_{ji}) > u_{hii}(m_i, m_i, 0)$. Furthermore, it will commute to a specific unit j if the utility from working there is higher than the utility it could achieve in any other regional unit, $u_{hji}(m_i, m_j, d_{ji}) = \max\{u_{hni}(m_i, m_n, d_{ni})\ \forall\, n \in I\}$. In this case, we observe individual h commuting from i to j, denoted by $b_{hji} = 1$, while $b_{hni} = 0\ \forall\, n \neq j$. Aggregating the choices of all H individuals in unit i leads to:

$$\sum_{h=1}^{H} b_{hji} = e_{ji}$$

e_{ji} is the aggregate number of individuals living in i but working in j, i.e., the flow of commuters from i to j. It can be assumed that the observed commuting flows are based on revealed preferences: each worker is actually working in the unit he can derive the highest utility from, given his preferences about the characteristics of the regional units m_i and m_j and the costs of commuting d_{ji}. At the aggregate level, the individual's preferences are not known, only the characteristics of the regional units can be observed.

Assuming that the individuals' preferences towards residence and workplace characteristics are similar within a commuting flow, the characteristics of the source and target units can be used to explain the mismatch of residence-workplace location combinations which leads to "voluntary" commuting in the sense that it is above the magnitude required to equilibrate the pure excess demand for (or supply of) local workers. A general commuting flow function can thus be represented by

[4] Commuting costs within a regional unit are assumed to be zero, i.e., $d_{ii} = 0$ if $i = j$.

$$e_{ji} = g(m_i, m_j, d_{ji}) \tag{1}$$

which describes the flow from i to j (e_{ji}) as a function $g(\cdot)$ of characteristics of the regional units involved (m_i, m_j) and the costs of commuting (d_{ji}). The flow of workers from i to j is restricted by the following constraints:

$$0 \leq e_{ji} \leq \min(a_i - e_{ii}, k_j - e_{jj}) \tag{2}$$

where a_i denotes the number of workers in the source municipality i, while k_j denotes the total number of jobs in the target municipality j.

3. Data

The Austrian province Vorarlberg acts as the region under investigation and the empirical analysis will be performed by taking municipalities as the base unit: the province consists of 96 municipalities, so that there are 9,120 distinct commuting flows. The data on commuting are taken from the latest Austrian census in 2001.

The upper part of table 1 provides an overview of the commuting flows.[5] On average, each municipality in Vorarlberg has about 35 out-commuting targets. The average flow size (of the non-zero flows) is 1.73 % of all employed living in a municipality and 3 % of all out-commuters, respectively. The largest flow (in percentage terms) is 60 % of a municipality's out-commuters. On average, 63.9 % of a municipality's employed population work in a unit different from their unit of residence. The numbers for individual municipalities range from 11.65 to 86.55 %. Overall, 81,106 of the 146,594 employed persons living and working in Vorarlberg[6] (about 55.3 %) do not work in their residence municipality, most of them (79,673) commute on a daily basis.[7]

However, 5,930 (about 65 %) of the 9,120 flows between the 96 municipalities are zero, leaving 3,190 non-zero flows ranging from 1 to 1,305 individuals. An inspection of the data shows that the number of zero observations increases with distance: only 10.5 % of all commuting flows between municipalities less than 10 kilometers apart are zero, while zero commuting can be ob-

[5] The figures presented in table 1 include individuals commuting on a daily basis only. Unless specified otherwise, "commuters" in the following discussion always refers to the number of workers who travel each day between their residence and workplace location municipalities. Workers who do not commute on a daily basis and those who commute within a municipality's boundaries are not considered.

[6] This figure also includes self-employed persons.

[7] There are also 13,917 additional commuters to foreign countries (mainly Switzerland, Liechtenstein and Germany) which are excluded from this figure, as are the 2,363 commuters to other provinces of Austria.

served for 97.6 % of all pairs with distances of 80 km or more. Zero observations are, however, not limited to long-distance relationships: while 30.1 % of all municipalities in the 10-19 km distance range have zero commuting, this percentage already rises to 51.0 % for municipalities 20-29 km apart, and even reaches 71.4% for municipalities 30-39 kilometers apart. This shows that there is a substantial percentage of zero-commuting pairs in the sample used, even at short distances. Taking this into account, including the zero observations in the regression analysis is important, because otherwise the distance parameter would be seriously underestimated (in absolute terms).

The independent variables used to explain the size of the place-to-place commuting flows can broadly be classified into the following categories: distance and remoteness as proxies for commuting costs, the attractiveness of source and target as a workplace location, population figures as well as local amenities and the provision of public goods in the regional units. Each of these categories and the corresponding variables will now be discussed in turn.

[Table 1 around here]

3.1 Distance and remoteness

Commuting costs are probably among the most important determinants of commuting choice. However, the direct costs of commuting are not observable at the aggregate level. The empirical analysis thus uses the distances between all 4,560 source-target combinations in kilometers as a proxy for the costs of commuting.[8] The data were surveyed using a route planner program and thus represent the actual road distances.[9] Summary statistics are shown in table 1. The average distance (in kilometers) between the municipalities is about 39 km. However, regional commut-

[8] The expected travel time was also surveyed and could be used as an alternative proxy for commuting costs. However, as time and distance are highly correlated (ρ=0.884), only distance will enter the empirical model. Average commuting speed was also surveyed, but the variable turns out insignificant in most estimations. Regression results including average speed are available from the author upon request.

[9] For some combinations of municipalities there is a trade-off between shortest and fastest route (this is especially true for municipalities which are not located close to each other): a faster but longer route is associated with lower time cost but higher vehicle cost compared to a slower but shorter travel. Since it is not clear how to weigh time and distance at the aggregate level, both were weighted equally to capture the trade-off.

ing mainly takes place at low distances: 75.4 % of all daily commuters travel less than 15 kilometers, 94.1 % less than 30 kilometers. The average commuting distance is 12.3 kilometers.

In addition, the average distance of a municipality to all other municipalities was computed to control for overall accessibility and remoteness of a prospective commuting target. Usually, a positive coefficient is expected for the remoteness variable (Frankel, 1998), although a negative sign could also be hypothesized so that there is less commuting the more remote (on average) the target community. Finally, a dummy variable captures whether source and target municipality are located in different districts[10], and a negative coefficient can be expected for this variable as well. Another variable which will enter the empirical application is a dummy measuring whether source and target municipality share a common border: 45.9 % of the commuters work in a neighboring municipality, so that a positive coefficient can be expected.

3.2 Attractiveness of source and target units as workplace locations

Another probably important set of characteristics is the relative attractiveness of the source and target municipalities as workplace locations. Again, the variables used here are shown in table 1. The percentage unemployment rate is supposed to discourage commuting as a target value, and to encourage commuting if it is taken as the source value. Unemployment rates range from zero to about 15 %, with a mean value of 4.3 %.

The labor market satiation (LMS) variable measures the extent to which local jobs are occupied by local workers and is defined as e_{ii}/k_i, where e_{ii} measures the number of workers living and working in regional unit i and k_i gives the number of jobs in i. The variable is assumed to enter the relationship with a negative coefficient as a target value (the more satiated the target municipality's labor market with workers residing there, the less jobs are available for workers residing in the source municipality), as a source value there is no a priori hypothesis about the sign of the coefficient: a high labor market satiation might reflect labor market tightness, i.e. that there is a shortage of vacant jobs for those who do not already work in their source community, thus encouraging out-commuting. On the other hand, a high labor market satiation could be responsible for low commuting, since most of the local workers have already found a job in their source municipality, so that drawing an a priori conclusion about the direction of the effect of labor market satiation as a source value is difficult.

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[10] The province of Vorarlberg is divided into the four districts Bludenz, Bregenz, Dornbirn and Feldkirch.

The number of workplaces with more than 500 employees can also be expected to have a positive effect on commuting: in the region under consideration, there are only 18 firms with more than 500 workers, and municipalities hosting one or more of these larger firms can be assumed to enjoy more in-commuting than other municipalities.

The level of employment—as a measure of the level of activity in the source and target municipalities—cannot enter the model directly, as it is nearly perfectly correlated with population (ρ=0.980). Therefore, employment is included in the model only indirectly through the ratio of jobs to workers (also labeled "import ratio", e.g., by Elwood, 1982) in a municipality (k_i/a_i, with a_i being the number of employed individuals living in i), which measures the relative importance of a municipality as a workplace relative to its importance as a place of residence. A municipality with a high value of jobs to workers can be assumed to provide more job opportunities and thus attract workers from a wider range of surrounding municipalities, so that a positive coefficient can be expected.

3.3 Population

The 2001 population will be used to control for municipality size. As can be seen from table 1, municipalities in Vorarlberg consist of about 3,650 residents on average, the largest being the town of Dornbirn with 42,301 inhabitants. According to the 2001 census figures, the region's total population is 351,095.

Data are also available on population characteristics in the municipalities, such as age, education and qualification patterns or marital status. Although there is empirical evidence on some characteristics from individual-level studies[11], formulating a priori hypotheses at the aggregate level is difficult. Furthermore, these variables characterize the population living or working in a municipality, but not the commuters themselves. Therefore, aggregate population characteristics are not

[11] Concerning age, Romaní, Suriñach and Artís (2003) for example report that workers under 25 years of age commute less than workers between 35 and 40 whereas those between 45 and 50 experience the highest commuting probabilities. On the other hand, estimations by Eliasson, Lindgren and Westerlund (2003) revealed that the probability of labor market related mobility decreases with age, a similar result was also found by Punpuing (1993). Romaní et al. found more years of education to be associated with a higher probability of commuting, and Eliasson et al. report that people with an upper-secondary school education or higher have a greater propensity to be mobile. Romaní et al. also estimated that the more skilled a professional category, the larger its commuting probability. Concerning marital status, they were able to estimate a lower commuting probability for widowers, whereas Eliasson et al. found single people more likely to be mobile.

included in the estimations because they do not necessarily describe the personal characteristics relevant for the commuting decisions of the individual workers.

3.4 Local amenities and local public goods

As one of the main points of this paper, the variables used to capture the supply of local amenities and local public goods are of special importance. These variables enter the model either as target-only dummy variables (where the dummy variable takes on the value 1 if the target location has a specific characteristic the source municipality does not have, and zero otherwise) or as target values (while controlling for the source value in the regression) and are listed at the bottom of table 1. Dummy variables indicate the existence of different types of public schools: while 41 municipalities (42.7 %) have elementary schools, there are only 10 municipalities with secondary schools (10,4 %). If the target municipality has a specific school type the source municipality does not have, there is an auxiliary utility of the commuting trip (e.g., bringing the kids to school) which increases the attractiveness of working in the target municipality. Therefore, target-only dummy variables for elementary and secondary schools are included, for which a positive coefficient can be expected.

The second part of table 1 focuses on public safety: the number of registered crimes per 1,000 inhabitants varies from about 11 to nearly 350[12], with an average of 50 registered crimes per 1,000 inhabitants.[13] This variable can be expected to exhibit a negative coefficient if it is taken as a target value (after controlling for the source value), so that a municipality with a higher crime level is less attractive as a commuting target.

The next part of the table shows variables reflecting the supply of health-related institutions. The first variable is a dummy taking on the value 1 if there is a nursing home in the municipality. Nursing homes for elder people can be expected to exhibit a positive effect on commuting, both as a source and a target value. Nursing homes act as substitutes for home care, enabling people to seek work outside the municipality who would otherwise work at their place of residence or exit

[12] In fact, there are only 4 municipalities with more than 100 crimes per 1,000 inhabitants. Apart from the province's capital, Bregenz (about 137 registered crimes per 1,000), the municipality with the highest number of crimes is a popular skiing resort with very few permanent inhabitants (and about 650 overnight stays per inhabitant, the second highest figure in Vorarlberg) which leads to the reasonable assumption that tourism-related incidents (e.g., theft of skiing equipment) push the figure.

[13] This figure represents registered crimes only, not all of them will have led to convictions. Furthermore, no distinction is made between different types of crimes, since the figures are not readily available at this level of aggregation.

the labor market, thus encouraging commuting. The number of general practitioners per 1,000 inhabitants[14] not only serves as a proxy for the level of health care services in a municipality, it might also be another source of an auxiliary utility of the commuting trip (especially since about 30 % of the municipalities do not have a general practitioner at all) and is therefore (after controlling for the level of health care services in the source municipality) expected to have a positive effect on commuting. The next variable is a dummy taking on the value 1 if the municipality is one of the 6 locations with a (public) hospital, for which a positive effect can be expected. Finally, the number of shops for convenience goods represents consumer amenities which can constitute another source of auxiliary utility, so that a positive effect can be expected here for the target value.[15]

4. Empirical model

These variables will be used in the empirical analysis to estimate the general commuting flow function (1). This function basically implies a "modified" (Greenwood, 1997) gravity model specification where the "gravitational force" (the flow between two units) depends not only on distance and "mass", measured by the population. While the population is included in the source and target country characteristics m_i and m_j, the gravity-like model is also extended by proxies for accessibility, measures of the attractiveness of the source and target unit as workplace locations as well as measures of local amenities and local public goods which are also included in m_i and m_j. One municipality will be excluded from the analysis because of data restrictions, leaving 95 municipalities and 8,930 associated pairs of which 3,145 have non-zero commuting flows. The empirical model is given by the following linear model:[16]

[14] The number of general practitioners includes only those in the public health system.

[15] Data on the number of shops were obtained from statistics of the Austrian Federal Economic Chamber.

[16] Using both source and target values of the attractiveness variables might seem odd at first, because some of these variables can also be expected to influence the residence location decision which is assumed to be predetermined to the workplace location decision. But, as is clear from the discussion in section 2, individuals compare amenities at their residence unit to amenities at their workplace location. It is thus necessary to control for the provision of amenities at the source municipality to capture the individual's decision process. The dependent variable is taken as is viz. it is not taken in logs (as is common in estimating flow variables) because of the zero observations. Estimation of the log-linearized formulation of the gravity model is, however, also discouraged by Santos Silva and Tenreyro (2006).

$$
\begin{aligned}
e_{ji} = X\beta = \quad & \beta_0 + \beta_1 \text{distance} + \beta_2 \text{distance}^2 + \beta_3 \text{avg. distance} + \beta_4 \text{different district} \\
& + \beta_5 \text{common border} + \beta_6 \text{unemployment rate}_i \\
& + \beta_7 \text{unemployment rate}_j + \beta_8 \text{LMS}_i + \beta_9 \text{LMS}_j \\
& + \beta_{10} \text{jobs} - \text{to} - \text{workers}_i + \beta_{11} \text{jobs} - \text{to} - \text{workers}_j \\
& + \beta_{12} \text{workplaces} > 500_j \\
& + \beta_{13} \text{elementary school (target} - \text{only)} \\
& + \beta_{14} \text{secondary school (target} - \text{only)} \\
& + \beta_{15} \text{crimes per } 1000_i + \beta_{16} \text{crimes per } 1000_j \\
& + \beta_{17} \text{nursing home}_i + \beta_{18} \text{nursing home}_j \\
& + \beta_{19} \text{general practitioners per } 1000_i \\
& + \beta_{20} \text{general practitioners per } 1000_j + \beta_{21} \text{hospital}_i \\
& + \beta_{22} \text{hospital}_j + \beta_{23} \text{shops}_i + \beta_{24} \text{shops}_j + \varepsilon_{ji} \qquad (3)
\end{aligned}
$$

The dependent variable—the commuting flows e_{ji}—is bilateral, but not bidirectional which amounts to using gross instead of net flows: for every combination of municipalities i and j there are two flows to be accounted for: e_{ji} and e_{ij}.

Furthermore, the analysis in this paper also focuses on the explicit inclusion of zero-commuting observations, thereby incorporating the constraints in equation (2).[17] In many applications, zero-flow observations are excluded in empirical analyses although, as for example Renkow and Hoover (2000, p. 277) annotated, "using only observations in which some commuting occurred ignores potentially important information". Excluding the observations with a zero value of the dependent variable discards the information contained in these observations and truncates the sample[18], which calls for appropriate econometric methods to estimate the commuting flow function (1).

As an OLS estimator applied to a truncated sample can be biased and inconsistent, a Tobit model will also be estimated using all 8,930 observations. Using a Tobit model to estimate flows in gravity models is not uncommon, especially in the international economics literature (see, for example, Soloaga and Winters, 2001), but also in estimating commuting flows (see, e.g., Shields and Swenson, 2000). However, consistency of the Tobit estimates hinges crucially on two impor-

[17] Although equation (2) also implies an upper limit to a commuting flow, this limit is never reached in the data.

[18] As mentioned in section 3, there is no commuting in 5,930 of the 9,120 possible source–target combinations.

tant assumptions about the error distribution: normality and homoskedasticity. The normality assumption in the Tobit model can be tested using the conditional moment test by Pagan and Vella (1989). If the test rejects the null hypothesis of normally distributed errors, the Tobit estimates will be inconsistent, which calls for an alternative, robust estimator. Powell (1984) suggests estimating the censored regression model by a semiparametric method known as censored least absolute deviations (CLAD), which is consistent even under conditions of nonnormality and heteroscedasticity (see also Chay and Powell, 2001).[19]

As the dependent variable e_{ji} can only assume non-zero integer values, count data models can be used as an alternative to the linear and censored regression models. E.g., the Poisson regression model (PRM) can be applied to the structural model

$$\mu_i = E(y_i|X) = \exp(X\beta)$$

where the X variables are the same as in equation (3). But the PRM assumption of equidispersion (i.e., the assumption that the conditional mean is equal to the conditional variance) is rarely met by real data which are often characterized by overdispersion, i.e. the conditional variance is larger than the conditional mean (see Greene, 2000, p. 884). Overdispersion can lead to a downward bias in the estimated standard errors, and thus to an overestimation of the significance of the variables (Cameron and Trivedi, 1986). The most common among the alternatives to the PRM which relaxes the equidispersion assumption is the negative binomial regression model (NBRM), which allows for unobserved heterogeneity among observations (Greene, 2000, p. 886). Since the two models are nested, a likelihood-ratio test can be used to test for overdispersion (Long, 1997). A significant test statistic indicates that the negative binomial regression model should be used instead of the Poisson regression model, as the latter would underestimate the standard errors.

Both models can, however, perform poorly if the data are characterized by a large number of zero observations, as is the case with the data at hand (see section 3). To model these "excess zeros", zero-inflated count models (see Lambert, 1992, Greene, 2000) can be used. In contrast to the

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[19] Estimating a CLAD model involves an estimation step (in which the model is estimated by LAD) and a recensoring step (where observations are dropped for which the LAD predicted values are smaller than the censoring point). These steps are repeated until the method converges, i.e., until recensoring is no longer necessary. As a consequence, the "final" CLAD estimator does not use the full number of observations. The (LAD) standard errors reported by the Stata statistics package used to estimate the model were shown not to be robust to violations of homoskedasticity or independence of the residuals by Rogers (1993), so that bootstrapped standard errors should be used to assess the significance level of the estimates. The standard errors presented herein were computed using 1,000 bootstrap replications.

general Poisson and negative binomial models, which assume that every pair of origin-target municipalities has—in principle—a positive probability of commuting, the zero-inflated count models divide the observations into two (unobserved) groups: an "always zero" group Z where there will never be a positive amount of daily commuting—so that $\Pr(e_{ji} = 0) = 1$ if a municipality pair $(j, i) \in Z$, e.g., because they are too far apart for commuting to be economically reasonable—and a second group $\neg Z$ where individual observations can have zero values, but the general probability of an observation having a positive count is non-zero, $\Pr(e_{ji} = 0) \neq 1$.

The zero-inflated Poisson regression (ZIPRM) or the zero-inflated negative binomial regression (ZINBRM) model the probability of membership in either group, $\Pr[(j, i) \in Z|W]$ where W is a set of covariates, using a logit or probit approach, and estimate the counts for those in the group $\neg Z$. Again, as the models are nested, a likelihood-ratio test can be used to discriminate between the zero-inflated Poisson and negative binomial regression models. As shown by Greene (1994), the PRM and ZIPRM are, however, not nested. The same holds true for the NBRM and ZINBRM. However, a Vuong (1989) test for non-nested models can be used to indicate whether the ZIPRM or ZINBRM should be preferred to the PRM or NBRM models (Greene, 2000, p. 891).

5. Estimation results and discussion

5.1 Linear and censored regression models

Table 2 presents the estimation results of the linear and censored regression models including the variables presented in section 4.[20] The OLS regression in the first column was estimated using the 3,145 non-zero source–target combinations only: the "truncated" sample used in this estimation thus discards part of the information contained in the full sample and is included for reference. The results of the Tobit model using all observations are shown in the second column of table 2. However, a test for normality indicates that the method may provide inconsistent results: Pagan and Vella's (1989) conditional moment test resulted in a test statistic of CM=962.76 with a P-value of 0.000. The null hypothesis of normally distributed errors can therefore be rejected at conventional significance levels.

[20] Standard errors were omitted for lack of space in table 2 and are available from the author upon request.

The preferred model is thus Powell's (1984) CLAD estimator. The differences between the estimation methods are huge: for example, the CLAD coefficient on distance is nearly four times higher than the Tobit estimate, and more than five times higher than the corresponding OLS estimate, suggesting that the OLS and Tobit methods underestimate the true effects of distance on the size of commuting flows. The discussion of the effects will therefore focus on the CLAD estimates.

Before discussing the effects it is, however, important to clarify the nature of the parameters reported for the Tobit and CLAD models in table 2. A Tobit model of an observed, censored variable y can be derived from

$$y_i = \begin{cases} y_i^* & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases}$$

based on the unobserved "latent variable" $y^* = X\beta + \epsilon, \epsilon \sim N(0, \sigma^2)$. The Tobit coefficients in table 2 represent the change in the expected value of this latent variable for a change in an independent variable x_k, $\partial E(y^*|X)/\partial x_k$. As the model is linear in y^*, the coefficients do not depend on the level of the independent variables. While the "unconditional" marginal effect on the observed flow size y, $\partial E(y|X)/\partial x_k$ or the "conditional" marginal effect $\partial E(y|X, y > 0)/\partial x_k$ would appear more appealing at first glance, one could think of the Tobit coefficients shown in Table 2 as being the effects on the "desired" amount of commuting, i.e., the amount that would prevail if the flows were not restricted from below. Furthermore, the "unconditional" effect can be decomposed into (see, e.g., Wooldridge 2002, p. 523):

$$\frac{\partial E(y|X)}{\partial x_k} = \beta_k \times \Pr(y > 0|X)$$

so the change in the expected observed value of y due to a change in x_k is given by β_k (the effect on the unobserved latent variable y^*) times the probability of the observation being non-zero. The reported Tobit coefficients thus resemble the "unconditional" effect if $\Pr(y > 0|X)$ is close to 1. The differences between the unconditional effect and the reported coefficients are thus smaller at lower distances (because the latter are associated with a higher probability of a flow being non-zero). One could therefore think of the reported coefficients as approximating the effects on observed commuting $E(e_{ji}|X)$ evaluated at low distances. The CLAD estimates can be interpreted in the same fashion as the Tobit coefficients (Wooldridge 2002, p. 536) and thus also represent the partial effects on the latent variable.

There are two reasons for reporting the effects on the unrestricted latent variable in the Tobit and CLAD models: first, the OLS regression without zero observations implicitly assumes that the dependent variable is not restricted from below, so that information from restricted observations is discarded completely. If no zero observations are included in the sample, the estimated effect β_k from a Tobit regression on the latent variable y^* reduces to the OLS estimate from a regression without zero observations. It is thus more natural to compare the OLS coefficients to the effects on the unrestricted latent variable of the Tobit regression.

Secondly, and probably more important, the "unconditional" and "conditional" effects cannot be calculated for the CLAD estimator (Wooldridge 2002, p. 536), which would make comparison between Tobit and CLAD infeasible. Thus, the effects on the "latent" variable are the only parameters which can be compared across all three models.

[Table 2 around here]

As expected, commuting is decreasing in the distance between municipalities which is used to proxy for the costs of commuting, but at a declining rate as can be seen from the positive coefficient of the squared distance variable which was included to capture nonlinearities in estimating the effect of an additional kilometer of distance.[21] The effect of the source and target municipalities being in different districts is, as expected, negative but only significant at the 10 % level in the CLAD model. The average distance of the source municipality to all other municipalities enters the estimations with a positive effect, while the coefficient of the target's remoteness is significantly negative: the more remote a target municipality, the less attractive it is as a commuting target. One possible explanation for the positive coefficient for the source value is that the more remote, the less attractive it is for firms to settle in the municipality, leading to higher out-commuting of local residents. Sharing a common border, as expected, increases commuting between municipalities. The coefficients of the CLAD model are substantially higher than the corresponding OLS or Tobit estimates. This is especially true for the distance (as discussed above) and average distance parameters: the coefficient of the latter is about 6 times the size of the Tobit

[21] This suggests that the effects will cancel each other out at a distance of about 133 kilometers (taking the CLAD estimates as a basis). But since, as discussed in section 3.1, nearly 95 % of all commuters travel less than 30 kilometers, it is unlikely that this effect will play a role in practice.

coefficient, and about 10 times that of the OLS coefficient. It thus can be asserted that the OLS and Tobit methods seriously underestimate the effect of the distance and remoteness variables.

The hypothesized positive effect of the unemployment rate at the source municipality is only significant if the model is estimated by CLAD: as expected, a higher unemployment rate at the unit of residence encourages out-commuting to other regional units. Surprisingly, the coefficient of the unemployment rate at the target municipality has a positive sign as well and is significant in the Tobit and CLAD models (albeit only at the 10 % level). This finding is not unparalleled in the literature (cf. Shields and Swenson, 2000) and may be due to an endogeneity problem: the more individuals commute to a municipality, the higher the competition for jobs there. This may—all else equal—lead to a larger unemployment rate. The satiation of the local labor market with local workers (LMS) has a negative effect on commuting in all three models if it is taken as a source value. The negative sign suggests that the variable captures the effect that most of the local workers have already found a job in their source municipality, and not the labor market tightness effect hypothesized in section 3.2. The negative coefficient of the target unit's labor market satiation variable is not significant if the model is estimated by CLAD. As expected, the ratio of jobs to workers at the target municipality has a significantly positive effect on commuting. The number of large firms (defined as workplaces which offer more than 500 jobs) in the target municipality does not significantly increase commuting in the CLAD model.

As expected, the source municipality's population (in 1,000) enters all three models with a significantly positive coefficient. However, the coefficient in the CLAD model is more than twice as large as in the OLS and Tobit models. Surprisingly, the effect of the target municipality's population is not significant in the CLAD model: the standard gravity model variable is only significantly positive in the OLS or Tobit estimations.

Controlling for the number of shops for convenience goods at the source unit, the effect of the number of shops at the target municipality is, as expected, significantly positive but only at the 10 % level in the CLAD model: the higher the supply of consumer amenities at the prospective target unit, the higher commuting to this municipality.[22] Looking at the variables capturing the provision of educational institutions, just the variable for an elementary school at the target only is

[22] However, the variable should be interpreted with care because of possible endogeneity problems. For example, a municipality with a large number of in-commuters may offer more amenities (e.g., shops) because of the additional demand created by the commuters themselves. Shields and Swenson (2000) also note a possible effect of the level of in-commuting on the demand for local public goods, however fail to provide more detailed empirical evidence.

significant in the CLAD model, but surprisingly the coefficients are all negative, contrary to a priori expectations. This suggests that, ceteris paribus, commuting flows from municipalities without to target municipalities with elementary schools are smaller. One possible explanation for this finding could be that communities without elementary schools are generally smaller, leading to smaller outflows on average. Public safety, measured by the registered crimes per 1,000 inhabitants, does also not significantly affect commuting. Considering the variables used to capture the supply of health-related institutions, the nursing home dummy turns out to be significant across all different models: a nursing home at the source or target municipality has a positive effect on the size of the commuting flow. The same holds true for hospitals in the source, but not in the target municipality. The number of general practitioners on the other hand shows the expected positive sign as a target value (after controlling for the number of general practitioners in the home municipality), but the effect is statistically insignificant.

The evidence for some of the amenity and local public good variables is thus less robust than for the "classical" variables measuring distance or labor market conditions. And although some effects seem quite impressive, especially in the preferred CLAD model, the relative size of the coefficients is put into perspective when they are compared e.g. to the distance variable. For example, if the number of shops for convenience goods at the target municipality increases by one, the number of commuters rises by about 8.3 persons on average (CLAD estimate). However, the number of commuters decreases by about 15.8 (also considering the quadratic term) persons if the distance increases by 1 km. In another example, the number of commuters is—ceteris paribus—82.1 persons larger if there is a nursing home in the target municipality, but 43.3 persons smaller if it is in another district. This shows that there is a large trade-off between public goods or amenities in the target municipality and travel costs, proxied by distance. However, one has to bear in mind that these coefficients are the effects on the unobserved latent variable, which can assume also negative values (in which case the observed variable would be zero).

5.2 Count data models

Table 3 shows the results of the Poisson (PRM) and negative binomial (NBRM) regression models, while table 4 gives the results of the zero-inflated Poisson (ZIPRM) and zero-inflated negative binomial (ZINBRM) models.[23] The reported parameters are the marginal effects on the ex-

[23] The disturbance terms in the (zero-inflated) negative binomial regression models are assumed to follow a Gamma

pected number of counts, $\partial E\left(e_{ji}\,|X\right)/\partial x_k$, evaluated at the mean of all independent variables (reported in the last column of table 3). The marginal effects in table 4 apply only to observations in the group $\neg Z$ where $\Pr\left(e_{ji}\, = 0\right) \neq 1$. Hence, they are not directly comparable to the coefficients of the linear or censored regression models presented in table 2.

Table 4 also shows the coefficients of the inflation equations of the zero-inflated Poisson and negative binomial models which estimate the probability $\Pr[(j,i) \in Z|W]$, where W is a set of covariates which determines membership in Z. The set of covariates W used in the inflation equation is the same as the one used in the count equation, X. A positive coefficient implies that the variable increases the probability of an observation being in the "always zero" group, and vice versa for a negative coefficient. The probability of membership in either of these groups is modeled using the logit formulation by Lambert (1992).

[Table 3 around here]

Testing for overdispersion using a likelihood-ratio test shows that the NBRM is preferred to the PRM ($G^2 = 24069.4$, P-value = 0.000),[24] while the ZINBRM is preferred to the ZIPRM ($G^2 = 20149.8$, P-value = 0.000). A Vuong (1989) test for the ZIPRM and PRM implies that the zero-inflated Poisson model is preferred ($V = 13.20$, P-value = 0.000), while the same test favors the zero-inflated negative binomial regression model over the NBRM ($V = 12.03$, P-value = 0.000). To sum up, the statistical tests show that the zero-inflated negative binomial regression is the favored model. The discussion of parameters will therefore focus on the results of the ZINBRM.

[Table 4 around here]

As in the models of section 5.1, the ZINBRM shows that the size of a commuting flow declines with distance, but at a decreasing rate. Municipalities in different districts also show a significant-

distribution. Standard errors are omitted from tables 3 and 4 and available from the author upon request.

[24] The coefficient on α in tables 3 and 4 measures the degree of overdispersion. If $\alpha = 0$, the NBRM reduces to the PRM (see Long,1997, p. 247).

ly lower level of commuting, while commuting flows are larger between neighboring municipalities. The positive coefficient for distance in the inflation equation shows that the probability of a municipality pair being in the "always zero" group increases the further apart the source and target municipalities, thus "amplifying" the negative effect of distance on expected counts. The combined probability of zero commuting—the probability of a municipality pair (i, j) being in the "always zero" group plus the probability of the count being zero, conditional on an observation not being in the "always zero" group, $\Pr[(j, i) \in Z|W] + \Pr[e_{ji} = 0|(j, i) \notin Z, X] \times (1 - \Pr[(j, i) \in Z|W])$—is estimated to be 6.8 % at a distance of 10 km, 25.1 % at a distance of 20 km and rises to 53.7 % and 75.9 % for municipalities 30 and 40 kilometers apart (holding all other variables are at their mean). This corresponds well with the structure of the data (see section 3) and shows that distance is—as expected—one of the most important determinants of commuting.

While the marginal effects on the observed number of counts in tables 3 and 4 seem small—especially compared to the coefficients of table 2—one has to bear in mind that these marginal effects are evaluated at the mean values of all variables, while—as noted in section 4—the coefficients of the Tobit and CLAD models can be interpreted as approximating the effects on observed commuting $E(e_{ji}|X)$ evaluated at low distances. Evaluating for example the marginal effect of distance in the ZINBRM at 1 kilometer yields -3.171, -1.766 at 5 km and -0.885 at 10 kilometers. However, one has to bear in mind that the marginal effects of the ZINBRM only apply to observations not in the "always zero" group Z, not to the whole sample.[25]

In contrast to the CLAD model unemployment at the source municipality is not significant in the ZINBRM, while unemployment in the target again enters the model with a positive sign.[26] The jobs-to-workers ratio in the target municipality, which measures the relative importance of a municipality as a workplace, has a significantly positive impact on the size of a commuting flow (while at the same time reducing the probability that a flow is always zero). As in the OLS and Tobit models of section 5.1, the labor market satiation has a negative influence on commuting, both at the source as well as at the target. Interestingly, the number of large firms in the target municipality (measured by the number of workplaces with more than 500 employees) has a nega-

[25] The marginal effect of distance in the non-inflated negative binomial model evaluated at 1 km is -16.016, -8.735 at 5 km and -4.094 at 10 km. These marginal effects apply to all observations are thus much closer to the effects from the CLAD and Tobit models of table 2.

[26] Again, this may be due to endogeneity problems.

tive effect on commuting in all count data models. The marginal effects are, however, negligible. As expected, the size of both the host and target populations (in 1,000) has a positive influence on the size of a commuting flow.

While the number of shops has no significant effect on the size of a commuting flow, the negative coefficient in the inflation equation shows that the probability of always observing a zero level of commuting decreases with the number of shops in the target municipality. E.g., the combined probability of zero commuting declines by 6.9 % if the number of shops in the target municipality increases from zero to five (holding all other values at their mean). This suggests that while consumer amenities at the target municipality do not significantly influence the number of commuters moving from i to j, they lower the probability of never observing any commuting to this target municipality.

As in the linear and censored regression models, the dummy variable for elementary schools at the target only is significant in the zero-inflated negative binomial regression, but enters the model with a negative sign. Again, this finding could be explained by the observation that communities without elementary schools are generally smaller, leading to smaller outflows on average. The dummy for secondary schools in the target only on the other hand shows the expected positive sign and has a significant effect on commuting flows in the Poisson and negative binomial regressions of table 3, but is not significant in the ZINBRM. The variables capturing the provision of educational institutions thus again show mixed results. Surprisingly, the number of registered crimes per 1,000 inhabitants significantly increases commuting if taken as a target value. The effect is, however, negligibly small: a standard deviation increase in the number of registered crimes (about 37 crimes, see table 1) increases the expected number of commuters by only 0.045 individuals in the ZINBRM (for those observations in $\neg Z$, holding all other variables at their mean). At the same time however, the variable also significantly increases the probability $\Pr[(j,i) \in Z|W]$: the lower public safety in the target, the higher the probability that no commuting will ever be observed for this pair of municipalities. Again, the effect is rather small: even an increase from zero to 100 crimes per 1,000 inhabitants in the target municipality raises the combined probability of zero commuting by only 2.6 %.

Turning to the proxies for the supply of health-related institutions, nursing homes at the target have a significantly positive effect on both the expected number of commuters, but also on the probability that a municipality pair is in the "always zero" group Z. Overall, the effect on commuting is, however, positive in the zero-inflated negative binomial model: while having a nursing home in the target increases the probability of never observing commuting by 5.1 %, the probability of observing a zero flow given commuting is possible, $\Pr[e_{ji} = 0|(j,i) \notin Z, X]$, decreases by 13.9 %. The combined probability of zero commuting thus declines by 11.1 % if there is a nursing home in the target municipality. This effect is, however, still rather small compared to the effect of distance.

The marginal effect of the number of general practitioners in the target municipality is not significant in the ZINBRM, although the variable significantly reduces $\Pr[(j,i) \in Z|W]$. As with the consumer amenity variable, the level of health care services (as proxied by the number of general practitioners) does not affect the size of a commuting flow (after controlling for the level in the source municipality), but increases $\Pr[(j,i) \notin Z|W] = 1 - \Pr[(j,i) \in Z|W]$, the probability that commuting is potentially observed. The marginal effect of a hospital in the target municipality is, in contrast to the linear and censored regression models in table 2, significant in the zero-inflated models, but negative. The variable appears with a positive sign in the PRM and NBRM estimations (albeit insignificant in the latter) and is thus not very robust to different model specifications.

6. Conclusions

In this paper, aggregate data for the Austrian province of Vorarlberg were used to estimate place-to-place flows of commuters between municipalities using a wide range of regressors and different estimation procedures, including linear and censored regression as well as count data models. The comparison between the linear and censored regression models shows that discarding the information contained in "zero" observations leads to large differences in the size of the estimates. E.g., the standard OLS method largely underestimates the effect of distance compared to the censored regression models. Considering zero observations using appropriate censored regression models is thus important especially if there is a large proportion of zero observations in the sample. As testing shows that the normality assumption of the applied Tobit estimation is violated, the paper also applies Powell's (1984) censored least absolute deviations (CLAD) estimator which is robust to violations of assumptions of normality and homoskedasticity. The differences between the inconsistent Tobit and the robust CLAD methods were shown to be substantial both in terms of size and significance. Testing among the count data models showed that a zero-inflated negative binomial regression model (ZINBRM) is preferred to the (zero-inflated) Poisson and negative binomial models because of overdispersion and due to the large number of zero observations in the sample.

In all estimated models, distance and remoteness (as proxies for the costs of commuting) affect commuting decisions at the aggregate level: commuting flows are declining in distance (although—as shown by the positive coefficients of the squared distance variables—at a decreasing rate) and higher for neighboring municipalities and communities within the same district. More remote municipalities experience less in-commuting but increased out-commuting, although the variable is not significant in all estimated models. It was shown that labor market conditions at the source and target municipalities significantly contribute to explaining flows of commuters: in all but the (zero-inflated) negative binomial models, commuting flows are larger the higher the unemployment rate at the source municipality, and the lower the satiation of the local labor market with local workers. In addition, a higher ratio of jobs to workers at the target also increases the size of commuting flows.

As far as local amenities and the spatially differentiated provision of local public goods are concerned, the results are somewhat mixed. Robust results can be found for consumer amenities, such as the number of shops at the target municipality, which are ceteris paribus another source of increased in-commuting. Even though the variable does not significantly increase the expected number of commuters, as is the case in the ZINBRM, the results suggests that consumer amenities increase the probability of potentially observing at least some individuals moving to a target municipality. The estimations also show that substitutes for home care such as nursing homes significantly contribute to explaining the magnitude of commuting flows.

Less robust are the findings concerning public safety, which does not significantly affect commuting in the linear and censored regression models while increasing the combined probability of zero commuting in the ZINBRM. The effects are, however, small at best. Unexpected results were found for the variables capturing the supply of educational institutions: a dummy variables for elementary schools at the target only is significant in the CLAD and zero-inflated negative binomial regressions, but enter the models with a negative sign which could be explained by the observation that communities without elementary schools are generally smaller, leading to smaller outflows on average. Among the proxies for the level of health care services, the ZIPRM and ZINBRM estimations show that the number of general practitioners per 1,000 inhabitants does not significantly affect the amount of commuting, but the variable significantly increases the probability that commuting is potentially observed. The variable is, however, not significant in all other models. The existence of hospitals in the target municipalities does not significantly affect commuting in the linear and censored regression models as well as in the Poisson and negative binomial models. The marginal effect is, however, significant in the zero-inflated Poisson and negative binomial models, but negative, in contrast to the a priori expectations.

For some of the local amenity and public goods variables, the evidence is thus less robust than for the "classical" variables measuring distance or labor market conditions. Furthermore, there is a large trade-off between public goods or amenities and other characteristics such as distance or the labor market situation. However, the paper shows that amenities and public goods can help to explain the level of commuting activities between municipalities.

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Variable	Mean	Std. Dev.	Min.	Max.
Commuting flows				
Commuting flows e_{ji} †	24.98	82.91	1	1305
% commuters $\left(e_{ji}/a_i\right)$ †	1.73	3.60	0.01	50.42
% commuters $\left(e_{ji}/\left(a_i - e_{ii}\right)\right)$ †	3.01	5.79	0.02	60.00
Distance and remoteness				
Distance ‡	38.84	21.07	1	133
Average distance ‡	38.84	9.12	27.82	87.69
Different district ‡	0.68	0.47	0	1
Common border ‡	0.06	0.23	0	1
Workplace location				
% unemployed	4.35	2.53	0	15.35
Labor market satiation (LMS)	0.51	0.19	0.16	0.93
Workplaces $>$ 500	0.19	0.71	0	4
Jobs-to-workers ratio	0.70	0.35	0.16	1.74
Population				
Population	3657.24	6327.64	147	42301
Amenities and local public goods				
Elementary school	0.43	0.49	0	1
Secondary school	0.10	0.31	0	1
Registered crimes per 1,000	49.39	37.22	10.94	347.20
Nursing home	0.41	0.49	0	1
General practitioners per 1,000	0.51	0.64	0	4.92
Hospital	0.06	0.24	0	1
Shops*	2.45	3.29	0	20

Table 1: Summary statistics, $n = 96$. † non-zero commuting flows ($n = 3{,}190$), ‡ municipality pairs ($n = 4{,}560$), * $n = 95$. e_{ji}: number of individuals living in municipality i but working in another municipality j. a_i: number of employed individuals living in municipality i. e_{ii}: number of individuals living and working in municipality i.

Variable	**OLS**	**Tobit**	**CLAD**
Distance and remoteness			
Distance	-3.353***	-4.277***	-15.948***
Distance^2	0.032***	0.029***	0.120***
Different district	-15.783***	-20.897***	-43.312*
Average distance	0.610**	1.013***	6.098***
Average distance$_j$	-0.152	-0.062	-7.008***
Common border	41.772***	39.622***	65.550***
Workplace location			
% unemployed	0.366	0.509	11.594**
% unemployed$_j$	0.830	1.471**	10.310*
LMS	-21.795**	-30.266***	-162.850**
LMS$_j$	-36.988***	-81.060***	25.093
Jobs-to-workers ratio	-2.813	0.174	-9.112
Jobs-to-workers ratio$_j$	26.706***	38.220***	163.711***
Workplaces > 500$_j$	5.513***	2.713*	4.618
Population			
Population (1,000)	3.502***	3.204***	8.195***
Population (1,000)$_j$	2.208***	3.575***	2.839
Amenities, local public goods			
Shops	-1.126	0.208	-2.387
Shops $_j$	3.276***	2.784***	8.296*
Elementary school (target-only)	-12.984***	-9.784***	-68.357***
Secondary school (target-only)	-30.946***	-23.435***	-9.177
Reg. crimes/1000	0.015	-0.000	-0.566
Reg. crimes/1000$_j$	0.008	0.028	0.398
Nursing home	9.373***	17.670***	70.671***
Nursing home$_j$	10.389***	19.492***	82.078***
General prac./1000	-0.960	0.756	-58.304**
General prac./1,000$_j$	3.865	3.547	11.531
Hospital	-4.956	-2.449	44.183**
Hospital$_j$	-1.137	-5.486	-3.654
Constant	16.641	-7.173	-176.227**
Observations	3145	8930	8930
(Pseudo-)R^2	0.371	0.134	0.421

Table 2: Coefficients of OLS, Tobit and CLAD regressions. Dependent variable: size of commuting flow (number of workers commuting on a daily basis) between municipalities. * significant at 10 %, ** significant at 5 %, *** significant at 1 % significance level. Significance level assessment in CLAD model based on bootstrapped standard errors using 1,000 bootstrap replications. j denotes values for target municipalities.

Variable	PRM	NBRM	Mean(X)
Distance and remoteness			
Distance	-0.092***	-0.061***	37.800
Distance^2	0.000***	0.000***	1821.650
Different district	-0.217***	-0.200***	0.681
Average distance	0.025***	0.016***	38.325
Average distance$_j$	-0.018***	0.001	38.325
Common border	0.203***	0.200***	0.056
Workplace location			
% unemployed	0.030***	0.000	4.332
% unemployed$_j$	0.064***	0.015***	4.332
LMS	-0.473***	-0.267***	0.504
LMS$_j$	-1.063***	-1.223***	0.504
Jobs-to-workers ratio	-0.055***	0.069**	0.696
Jobs-to-workers ratio$_j$	0.872***	0.551***	0.696
Workplaces > 500$_j$	-0.045***	-0.050***	0.189
Population			
Population (1,000)	0.026***	0.026***	3.646
Population (1,000)$_j$	0.032***	0.044***	3.646
Amenities, local public goods			
Shops	0.023***	0.004	2.453
Shops $_j$	0.024***	-0.003	2.453
Elementary school (target-only)	-0.230***	-0.043***	0.246
Secondary school (target-only)	0.046***	0.074***	0.095
Reg. crimes/1000	-0.002***	0.000	49.281
Reg. crimes/1000$_j$	0.000***	0.001*	49.281
Nursing home	0.366***	0.252***	0.400
Nursing home$_j$	0.608***	0.316***	0.400
General prac./1000	-0.034***	0.020	0.514
General prac./1,000$_j$	0.020	0.027	0.514
Hospital	0.236***	0.099**	0.063
Hospital$_j$	0.149***	0.003	0.063
α		0.777***	
Observations	8930	8930	
Log-likelihood	-23704.24	-11673.52	

Table 3: Marginal effects on expected number of counts at the mean, Poisson and negative binomial regressions, and mean values of independent variables. Dependent variable: size of commuting flow (number of workers commuting on a daily basis) between municipalities. * significant at 10 %, ** significant at 5 %, *** significant at 1 % significance level. j denotes values for target municipalities.

Variable	ZIPRM	Inflation (ZIPRM)	ZINBRM	Inflation (ZINBRM)
Distance and remoteness				
Distance	-0.124***	0.155***	-0.084***	0.208***
Distance^2	0.001***	-0.001***	0.000***	-0.002***
Different district	-0.382***	0.612***	-0.231***	0.664***
Average distance	0.029***	-0.024***	0.025***	-0.035**
Average distance$_j$	-0.001	-0.047***	0.002	-0.071***
Common border	0.417***	-0.612***	0.319***	-0.427
Workplace location				
% unemployed	0.022***	0.019	0.000	0.013
% unemployed$_j$	0.039***	0.047**	0.018***	0.057
LMS	-0.618***	0.642*	-0.336***	-0.600
LMS$_j$	-1.372***	2.585***	-1.679***	-1.176*
Jobs-to-workers ratio	0.019	-0.299	0.072	-0.185
Jobs-to-workers ratio$_j$	1.091***	-1.204***	0.735***	-2.160***
Workplaces > 500$_j$	-0.095***	0.234**	-0.050***	-0.422
Population				
Population (1,000)	0.037***	-0.041*	0.041***	-0.477***
Population (1,000)$_j$	0.190***	-0.560***	0.085***	-1.303***
Amenities, local public goods				
Shops	0.035***	-0.072*	0.012	-0.247**
Shops $_j$	0.085***	-0.215***	0.008	-0.418***
Elementary school (target-only)	-0.312***	0.375***	-0.148***	0.111
Secondary school (target-only)	-0.067	0.230	0.050	0.996
Reg. crimes/1000	-0.001**	0.000	0.000	0.002
Reg. crimes/1000$_j$	0.000	0.001	0.001***	0.010***
Nursing home	0.484***	-0.588***	0.291***	0.131
Nursing home$_j$	0.330***	0.348***	0.362***	1.085***
General prac./1000	0.045	-0.392***	-0.010	-0.244
General prac./1,000$_j$	0.060	-0.347***	-0.044	-0.882***
Hospital	0.191**	0.013	-0.233	3.631**
Hospital$_j$	-0.642***	3.781***	-0.596***	12.809***
α			0.583	
Observations	8930		8930	
Log-likelihood	-21429.79		-11354,83	

Table 4: Marginal effects on expected number of counts at the mean and coefficients of inflation equations, zero-inflated Poisson and zero-inflated negative binomial regressions. Dependent variable: size of commuting flow (number of workers commuting on a daily basis) between municipalities. * significant at 10 %, ** significant at 5 %, *** significant at 1 % significance level. j denotes values for target municipalities.

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