A SPATIAL ANALYSIS OF DISAGGREGATED COMMUTING DATA:
IMPLICATIONS FOR EXCESS COMMUTING, JOBS-HOUSING BALANCE,
AND ACCESSIBILITY

DISSERTATION

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ABSTRACT

In the standard analysis of jobs-housing balance and excess commuting, the analyst seeks a matching between supposedly homogeneous workers from a place of residence to a place of employment. Unfortunately, much of the analysis to date on commuting deals with total commuting flow, undifferentiated with respect to worker and job characteristics. Measures based on undifferentiated workers often produce misleading results because the assumption of worker homogeneity is violated. Motivated by the needs of differentiating worker types, this dissertation employs a benchmark spatial modeling approach to disaggregating journey-to-work data by type of workers.

The objectives of this dissertation are: (1) to develop a trip distribution model disaggregating journey-to-work data by type of occupation to predict average actual commutes; (2) to develop a disaggregated version of a linear program to measure theoretical minimum commutes; (3) to investigate accessibility and its changes by occupation; and (4) to assess multiple relocation policy scenarios considering intrazonal, inbound, and outbound commuting flows.

All models presented in this dissertation are applied to the tri-state area combining counties across Indiana, Kentucky, and Ohio over the ten-year period between 1990 and 2000. Empirical results verify the existence of variations in the levels of excess commuting, jobs-housing balance, and accessibility by type of occupation. Workers in each occupation react differently to relocation policy scenarios with varying preferences in terms of reduction in minimum commutes.

This dissertation explicitly addresses the disaggregation issue in terms of job and worker heterogeneity and provides a benchmark approach for incorporating such details into the analysis of commuting. The proposed benchmarking models are expected to have a wide range of applications in measurement and assessment of empirical patterns of commuting. The scope of the disaggregation can be extended to other targets such as different types of industry, household structure, income level, ethnic background, education level, transportation mode, and gender. Further dimensions of disaggregation can address spatial interactions of different socio-economic groups in urban areas, and more generally, contribute to exploring urban sprawl with respect to job characteristics and industries.
DEDICATION

To Seonim and Matthew Joon
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CHAPTER 1 INTRODUCTION

The study of commuting has a long tradition in geography and other disciplines including city and regional planning, urban economics, urban sociology, and regional science. Researchers have studied between people’s commuting behavior and its impacts on the spatial structure using a variety of analytical methods. Owing to advanced spatial analysis methods accelerated by the development of Geographic Information Systems (GIS), much broader topics have been investigated.

This research enhances the geographic tradition of commuting research by developing a set of spatial modeling techniques for trip distribution estimation. The main focus of this research is to provide a benchmark approach that disaggregates journey-to-work data by worker type. Implications are discussed in the context of excess commuting, jobs-housing balance, and accessibility. By explicitly addressing the disaggregation issue by worker type, this research opens possibilities of future research directions. In order to provide a comparative view over the ten-year period between 1990 and 2000, US counties in the tri-state area of Indiana, Kentucky, and Ohio are selected for empirical study in this dissertation.
1.1 Research background

For the last several decades, metropolitan suburbs in the US have grown more substantially than central cities (Census Bureau 2002). The suburban population has increased from 37.6% in 1970 up to 50% in 2000 of total population while the central city population has remained around 30% (Census Bureau 2002). This dramatic suburban growth implies sprawl as people move farther away from downtown areas to seek a more comfortable environment. These moves are aided by and necessitate improvements of the transport system owing to the increase of automobile ownership (Downs 1992, Zhang 2001). The rapid suburban growth results in spatial separation of residence and employment locations (Cervero 1989a and 1991, Giuliano 1991, Horner 2004), which requires people to travel more to reach their jobs. Locational imbalances cause negative impacts on commuting by generating longer commutes, greater traffic congestion, higher energy consumption, and polluting the air (Bookout 1990). Commuting is bound tightly with spatial structure in that the spatial disparity between workers’ jobs and residences may alter people’s journey-to-work behavior. At the aggregate level, regional commuting efficiency has deteriorated and become a national concern (Haynes 2000, Horner 2002). Therefore, addressing the issue of commuting efficiency from a spatial perspective may have implications for aggregate regional welfare.


A primary concern of this dissertation is the broad scale analysis of the intrinsic amounts of spatial interaction needed to match workers to places of employment, choosing to disaggregate zonal data by worker type rather than the individual household level. At one extreme, little or no commuting would be required if people lived and worked in the same area under the perfect match of job and worker characteristics (Bookout 1990, Cervero 1989a, 1991, Giuliano 1991). In this theoretical state, excess commuting is minimized and ‘self-contained balance’ is achieved. At the other extreme, the absence of jobs in
some areas requires workers to make a journey-to-work trip to other areas, which contributes to the high levels of commuting observed in the US (Federal Highway Administration 2003). A major argument is whether jobs-housing policy is an effective planning tool to achieve commuting efficiency (Cervero 1989a, 1991, 1996a, Giuliano 1991). In spite of skepticism surrounding this jobs-housing balance policy (Giuliano 1991, Downs 1992, Giuliano and Small 1993), the effectiveness of this policy has been strongly supported by others as a way to achieve sustainability of commuting (Cervero 1989a, 1991, 1997, Peng 1997, Sultana 2002, Horner and Murray 2003). While there are two sides to this argument, the merits of the arguments cannot be gauged without disaggregating journey-to-work data by worker type.

In the standard analysis of jobs-housing balance and excess commuting, the analyst seeks a matching between supposedly homogeneous workers from a place of residence to a place of employment. Measures of excess commuting based on undifferentiated workers often produce misleading results because the assumption of homogeneity is violated in real cities (Harris and Ullman 1959). For example, it is possible that jobs in a medical district (which are presumably filled by doctors, nurses and medical technicians) could be erroneously matched to a nearby neighborhood where the predominant workforce is employed in manufacturing. Therefore, in order to make jobs-housing balance policy an effective planning tool to achieve commuting efficiency, worker and job characteristics must be taken into account. In matching a worker from origin $i$ (place of residence) to destination $j$ (place of employment), it is necessary to analyze the suitability of that worker to the jobs at that particular destination. Unfortunately, much of the analysis to
date on this topic has not had access to appropriately disaggregated spatial interaction data in terms of job and worker heterogeneity. Basic questions such as “where are the service jobs?”, “do service workers commute more efficiently than professional specialty workers?”, and “which zones have surplus or shortage of service jobs?” cannot be fully answered without disaggregating journey-to-work data. For example, in the well-known spatial mismatch literature, emerging evidence points to the need for extreme commutes by low income workers who cannot afford the residential locations close to their place of work (Horner 2004, Ihlanfeldt 1994, Immergluck 1998, Kain 1992).

This dissertation explicitly addresses the disaggregation issue by worker type in the commuting context. This dissertation intends to predict, assess, and identify varying levels of excess commuting, jobs-housing balance, and accessibility by occupational group both in 1990 and 2000. The objectives in this research are: (1) to develop a trip distribution model disaggregating journey-to-work data by type of occupation to estimate actual commutes; (2) to develop a disaggregated version of a linear program (LP) to measure theoretical minimum commutes; (3) to model and visualize patterns and changes of accessibility by worker type, and (4) to extend a linear program (LP) to assess multiple planning policy scenarios by imposing different restrictions on the diurnal shift of workers. All objectives are discussed as a way to verify occupational variations in accessibility, jobs-housing balance, and excess commuting using the analytical results from the proposed models.
1.2 Contributions of the research

This research emphasizes the importance of disaggregated journey-to-work data by type of occupation and contributes to commuting research in several ways. First, it is anticipated that the proposed benchmark approach will enhance the understanding of the relationships between commuting behavior and spatial structure in greater detail. Disaggregated models explicitly address job and worker heterogeneity, which has been a big issue in the past. Much of the analysis to date on commuting deals only with total commuting flow, undifferentiated with respect to job characteristics. Disaggregating commuting data by worker type will help explain different layers of a spatial system through the identification of location mismatch between residential and employment locations. Second, the scope of the disaggregation may be further extended to other targets such as industry, household structure, income level, ethnic background, education level, transportation mode, and gender. Third, a comparative view over the ten-year period from 1990 and 2000 will capture the temporal trends of commuting. Testing generality across multiple regional or urban settings seems to be an obvious extension of this work. Further investigation would be the hypothesis testing of relationships between excess commuting and occupational groups for a larger area and for a variety of city sizes. It is expected that this testing may be highly instructive especially in cities that have special contextual situations. Fourth, county level analysis will provide a more comprehensive view on urban sprawl by catching growing levels of interactions between urban counties and suburban or rural counties. Fifth, from the policy standpoint, controlled experiments of multiple policy scenarios will provide new insights on
assessing possible outcomes of a regional planning scheme. By doing so, it may be possible to estimate trade-offs between positives and negatives of a policy on the zonal basis as well as on the occupational basis. Moreover, it may be evaluated more specifically where more jobs need to be created or relocated and how many workers are contributing to excess commuting as a result of a specific policy. One needs to address how dynamically workers move in a diurnal cycle since the worker shift ratio can be incorporated into explaining different geographical contexts. Finally, this research considers the diurnal shifts of commuting acknowledging that the promotion of self-containment can be beneficial to reduce commuting distances (Cervero 1996a).

1.3 Limitations of this research

This dissertation opens some possibilities for future research directions. Due to the inconsistency of geographical units between 1990 and 2000 census data, only county level analysis is conducted. An obvious extension of this research would be a wide range of studies on the detailed urban structure. An analysis at a smaller scale, such as traffic analysis zone (TAZ) level, would be valuable to explore urban scale variations. In addition, combinations of a county level analysis with a TAZ level analysis would provide a more comprehensive view on detecting hidden trends and may have implications for the linkage between urban land use and transportation policies both at the regional and urban scales.
1.4 Organization of the research

Chapter 1 has introduced the topics and issues that will be discussed in this dissertation. Main topics surround the excess commuting, jobs-housing balance, and accessibility through the applications of spatial modeling and GIS. The vital component in this research is the disaggregation issue by worker type. By disaggregating journey-to-work data as a benchmark approach, it is expected that further disaggregation by other socio-economic groups is possible.

Chapter 2 reviews a body of literature relevant to later chapters. The first section introduces the concept of excess commuting focusing on two main streams of the methodological development. The second section reviews the literature on the concept of jobs-housing balance focusing on its effectiveness as a planning tool. The third section presents the concept of accessibility and its implications in a planning paradigm contrasting accessibility planning and mobility planning. The fourth section discusses the diurnal shift of workers that will be explicitly dealt in the chapter 6. The fifth section reviews modifiable areal unit problem with the notion of impacts of scale and unit definition on the geographical research. The sixth section discusses the relationships between transportation and land use in the context of travel behavior and spatial form. The seventh section explains modeling approaches including spatial interaction models and a linear program that are particularly relevant in this dissertation.
Chapter 3 extensively discusses study area and data. The tri-state state area including Kentucky, Indiana, and Ohio, is selected as a research area. Then the main data source of this research, Census Transportation Planning Package (CTPP) is described in detail. Three data parts in CTPP, occupational classification system, and consistency in geographic units in 1990 CTPP and 2000 CTPP are explained as they pertain to this research.

Chapter 4 presents two trip distribution models that disaggregate the aggregate commuting flow to individual commuting flows differentiated by worker type. The first model takes an information minimizing method and predicts average commute lengths for each occupation defined by CTPP. The second model employs a linear program, which optimizes the best possible commuting pattern of workers for each occupation while preserving the aggregate information given by CTPP. The information minimization (IM) model and a linear program (LP) are applied for the tri-state counties both in 1990 and 2000. Empirical results are then discussed in the context of excess commuting and jobs-housing balance emphasizing the needs of disaggregating commuting flow by occupation.

Chapter 5 examines the changes of county accessibility over the two census years. Balancing factors obtained from the information minimization (IM) model in the chapter 4 are used as surrogates for accessibility measures specifying residential accessibility and employment accessibility, respectively. Both 1990 and 2000 data are also used to
investigate temporal changes of accessibility at the county level. All accessibility scores are explained in terms of worker types to detect occupational variations.

Chapter 6 presents several planning policy scenarios. 5 scenarios are implemented under the worker relocation policy and the other 5 scenarios are assessed under the job relocation policy. Those scenarios are experimented in order to assess the impacts of the worker shift ratio and intrazonal work trips on the commuting pattern. A general idea is to examine occupational variations in minimum commutes if the total intrazonal commuting is maintained and certain restrictions on the worker shift ratio are imposed on each policy scenario. Using 2000 CTPP data, newly developed models are implemented to assess policy outcomes according to worker types. Consistent with two previous analysis chapters, this chapter provides new insights to explore dynamic aspects of commuting with considerations of outbound and inbound commuting in the jobs-housing balance framework.

Finally, chapter 7 summarizes major findings in analysis chapters in the dissertation. Contributions to the future research are discussed in the context of central concepts of this research.
CHAPTER 2 LITERATURE REVIEW

This chapter intends to provide a general review of the literature pertaining to topics of this dissertation. The three major concepts of excess commuting, jobs-housing balance, and accessibility are reviewed in the first three sections. Then diurnal population shift is introduced followed by analytical methods in commuting research focusing on modeling techniques. Spatial interaction models and a linear programming approach are discussed as trip distribution models. Since the primary research issue is on disaggregating journey-to-work data by occupation, this chapter touches upon the issue of differentiating worker types, as it is relevant to clarify the research gaps in the literature.

2.1 Excess commuting

Excess commuting can be defined as the difference between the observed average trip length and the theoretical minimum average length (White 1988, Small and Song 1992):

\[
\text{Excess Commuting} = \left( \frac{T_a - T_r}{T_a} \right) \times 100
\]

where \( T_a \) = observed average commute and \( T_r \) = theoretical minimum average commute.
Excess commuting reflects the surplus of journey-to-work travel caused by the locational mismatch of residence and employment locations. The observed commuting length is assumed to be non-optimal due to the disparity of job and home locations, which implies jobs-housing imbalance. As jobs-housing balance is promoted, the spatial separation between job and housing locations is expected to diminish, which in turn reduces excess commuting (Scott et al., 1997).

Hamilton (1982) and White (1988) contribute to two main methodological streams in excess commuting research. Hamilton (1982) first addresses the issue of “wasteful commuting” and tests the reliability of the standard monocentric model of urban economics in predicting journey-to-work patterns. By calculating mean and minimum commutes from the exponential density function, Hamilton finds that the actual average commute is greater than the theoretical average minimum length. Based upon this, he labels the difference between the actual average commute and the theoretical minimum commute as “wasteful”. For 14 US cities and 27 Japanese cities, Hamilton’s results show that almost 90 percent of urban commuting is “wasteful,” suggesting that reassigning workers to other employment locations may reduce excessive commuting (Hamilton 1988).

Hamilton’s results are biased upward and have been challenged by others questioning the suitability of his model (White 1988, Small and Song 1992, Horner 2002). Among them, White (1988) criticizes the poor quality of Hamilton’s model and argues that the monocentric urban economic model is not appropriate to explain the complicated urban
structure. White (1988) proposes an alternative way to calculate the theoretical average commute length ($T_r$). White (1988) adopts a linear programming (LP) approach that assigns workers to jobs, such that the average zonal commuting time is minimized. The transportation problem is formulated as follows:

\[
\text{Minimize} \quad T_r = \frac{1}{W} \sum_i \sum_j T_{ij} Y_{ij}
\]

subject to

\[
\sum_j T_{ij} = D_j \quad \forall j
\]

\[
\sum_i T_{ij} = S_i \quad \forall i
\]

\[
T_{ij} \geq 0 \quad \forall i, j
\]

where $W =$ total number of commuters, $T_{ij} =$ total work trips from zone $i$ to $j$, $S_i =$ total number of workers residing in zone $i$, $D_j =$ total number of workers employed in zone $j$, and $Y_{ij} =$ travel costs between zone $i$ and $j$.

The LP approach, proposed by White (1988), has been widely used and updated for the last two decades (examples and reviews include Giuliano and Small 1993, Scott et al. 1997, Scott and Getis 1998, Buliung and Kanaroglou 2002, Horner 2002, Horner and Murray 2003, Rodriguez 2004). Horner (2002) makes a notable extension to the concept of excess commuting motivated by an idea of the capacity paradigm. Horner argues that the accurate status of excess commuting may be misinterpreted if only the minimum
average length is compared with the actual commute length. Through the application of
the maximization concept as the upper bound of the commuting capacity, Horner
provides an idea that excess commuting can be represented according to the degree of the
consumed capacity. Commuting capacity is calculated as a range between the theoretical
minimum and maximum commuting lengths. While equation (2.2) minimizes the average
commute, the following estimates the maximum average commute as the upper bound, or
the worst situation of the regional commuting pattern:

$$\text{Maximize } T_r = \frac{1}{W} \sum_i \sum_j T_{ij} Y_{ij}$$  \hspace{1cm} (2.6)$$

While there have been some partial efforts to address the disaggregation issue in
commuting research, prior work addresses this issue in only a limited way (Giuliano
required commutes differentiated by 7 occupational groups. Service workers appear to
have the lowest minimum average commutes (8.16 miles), in contrast to the highest
highlights the needs for disaggregate commuting analysis by taking gender and 14
occupational categories into account. Horner finds that male workers in the armed forces
have the lowest minimum average trip length, followed by male service workers. These
two studies identify the existence of variations in commutes by socio-economic factors.
However, these two studies are not consistent between minimum commutes in
disaggregate analysis and those in aggregate cases. In Giuliano and Small (1993) the required commutes are computed separately for each category, which may produce different results when the aggregate data is directly applied. Similarly in Horner (2002), the minimum commutes in the disaggregate analysis are greater than those in aggregate case. To resolve this problem, the total number of workers should be controlled for. Since it is assumed that locations of jobs and workers’ residences are fixed in the cost minimization framework, the sums of workers in each category in an area should be consistent with the aggregate flow. This issue will be addressed in the following analytical chapters.

Kim (1995) incorporates household structure in excess commuting by considering two-worker households in Los Angeles. Cropper and Gordon (1991) use micro data for Baltimore, Maryland, and estimate household utility function by including neighborhood amenity as one of the independent variables. Rodriguez (2004) has reported an analysis using disaggregated data of bank tellers in Bogotá, Colombia, and shows deviations from minimum commute due to the temporal and structural constraints. Clark and Huang (2004) deal with disaggregated data for Seattle and show that both one- and two-worker households with greater separation between residence and employment tend to reduce commuting distance and time once a residential move is made. Buliung and Kanaroglou (2002) have some success in differentiating workers by two groups according to the 8 scenarios considering gender and household compositions. Using a modified excess commute measure for Toronto, Canada, they find that male auto-drivers are expected to have the largest excess commute.
2.2 Jobs-housing balance

The relationship of jobs-housing balance with commuting and spatial structure has been a major subject of a large body of literature. Jobs-housing balance has been defined as “the spatial relationship between the number of jobs and housing units within a given geographical area” (Peng 1997). An area is assumed balanced when workers can both live and work in that area. The ratio of the number of jobs to the number of workers in an area has been a typical measure (Bookout 1990, Levine 1998). Conventionally, jobs–housing balance has been calculated as follows. The number of resident workers often replaces the number of housing units assuming one worker per household (Bookout 1990):

\[
P_i = \frac{E_i}{H_i}
\]

(2.7)

where, \( P_i \) = the ratio of jobs to workers for zone \( i \), \( E_i \) = total number of jobs at zone \( i \), and \( H_i \) = total number of workers at zone \( i \).

If \( P_i = 1 \), a zone has the equal number of jobs and worker and it implies a balanced situation. In the case of \( P_i > 1 \), the quantity of jobs exceeds that of workers in zone \( i \) indicating surplus of jobs or a “job-rich situation”. Job-rich areas tend to attract a large number of workers from external zones. Employment centers such as central business district (CBD) or newly developed suburban office or shopping centers are good examples. A situation of \( P_i < 1 \) can be applied to residential areas where low-density land use patterns are dominant. In this case, longer commuting to job locations is expected.
The objective of jobs-housing balance policy is to reduce the spatial separation of workplaces and residences, which is expected to shorten average commuting distances (Scott et al. 1997). A major argument has been on whether jobs-housing balance policy is an effective planning tool to achieve commuting efficiency, therefore, a desirable urban form (Cervero 1989 and 1996a, Giuliano 1991, Downs 1992).

Giuliano (1991) and Downs (1992) are skeptical about benefits of improving jobs-housing balance. Downs (1992) argues that the strategy promoting jobs-housing balance may not be helpful to reduce traffic congestion due to the difficulty in removing existing imbalances and possibilities of other alternatives to lessen traffic congestion. However, Downs does not deny the effects of balancing jobs and housing to achieve social benefits. His argument is somewhat limited in that traffic congestion is considered as the only objective, which ignores a possibility of underestimated positive outcomes of jobs-housing balance. Giuliano (1991) thinks of jobs-housing balance as a process of urban growth, which is eventually achieved as a natural result. She insists that jobs-housing balance is not an efficient way to analyze traffic congestion and air pollution. Summarizing criticisms against jobs-housing balance policy, Giuliano states that proximity to workplaces cannot guarantee reduced commuting because relatively lower housing costs in suburban areas can compensate additional travel costs. On the same line, Giuliano and Small (1993) claim that jobs-housing balance policies might have little impact on commuting due to the little linkage between jobs and housing, both of which have their complicated nature.
A number of counter arguments have been made against the skepticism of the jobs-housing balance policy. While Downs and Giuliano address the mobility aspect emphasizing traffic congestion, the social benefits of jobs-housing balance are obtained by enhancing accessibility levels, not by reducing congestion. Enhancing accessibility might save social costs than improving mobility (Cervero 1997, Levine 2002) since planning policies that encourage the ease of car movement have accumulated urban sprawl and pollution (Cervero 1997). In this context, reducing congestion may not be an ultimate goal of the urban transport planning (Levine 2002). A congestion issue should be mentioned once the accessibility concept is incorporated into planning policies. Cervero (1996a) points out that there are misunderstandings about the real meaning of jobs-housing balance. He states that the purpose of balancing locations of jobs and housing is to break down the barriers against residential mobility, not to force people to choose their job and housing locations.

Peng (1997) conducts research on the relationship between jobs-housing ratio and vehicle miles traveled (VMT) for Portland, Oregon. Pointing out the limitations of macro and micro-scale analyses, he sets the actual average commuting distance as an alternative range for meso-scale analysis. Results show that jobs-housing balance has a nonlinear relationship with VMT. When the ratio is less than 1.2 and over 2.8, VMT shows noticeable changes. Two weaknesses in Peng’s research can be mentioned. First, actual average commuting distance used for his geographical scale is not investigated along with ‘minimum average commute’. Considering that jobs-housing imbalances cause “excessive commuting” or “wasteful commuting” (Giuliano and Small 1993), minimum
average commute where unnecessary trips are avoided should have been explained in a
comparison to actual VMT. Second, like much of earlier work, his research is relying on
an assumption that jobs-housing balance will shorten commuting distance. However,
commuting distances should be addressed along with the degree of the spatial mismatch
and the levels of self-containment. This assumption has been argued as one of problems
in the mobility planning (Cervero 2002, Levine 2002).

Scott et al. (1997) examine the impacts of commuting efficiency on reductions in
congestion and automobile emissions. The effects of excess commuting on the levels of
emissions of HC, CO, NOx, and congestion are inspected based on a comparison between
estimated and optimal commuting flows for Hamilton CMA (Census Metropolitan Area)
in Canada. They find that the efficient commuting pattern in the optimal scenario reduces
congestion, which is calculated as the ratio of link volume to link capacity. Emission
levels of HC and CO are improved as congestion level decreases. Although a possibility
of reductions in congestion and emissions is recognized, the effectiveness of jobs-housing
balance is not strongly supported. At the regional level (municipal level), jobs-housing
ratio does not show correlations with excess commuting.

One of challenges with the concept of jobs-housing balance, and implementing jobs-
housing policy has been measuring jobs and housing ratio and setting up desirable range
of the ratio. Using conventional jobs-housing ratios for policy targets may have flaws
because of those ratios cannot ensure the self-containment at local level (Cervero 1996a).
Even in a balanced situation from a conventional approach, commuting within the
community is much less than outbound commuting because jobs-housing balance is closely related with higher intrazonal commuting rates (Cervero 1996a). As a way to overcome this issue, an alternative way using an accessibility concept has been applied (Levinson 1998, Wang 2001). Levinson (1998) argues that relative residential and employment locations affect commuting duration. He finds that accessibility to jobs and housing has a negative relationship with distance, and that transit commuters appear to have higher accessibility than automobile users. Using the jobs-housing balance measure based on accessibility, he concludes that improving the balance would reduce commuting time. Levinson is among a few who address the importance of accessibility in the context of jobs-housing balance. Levinson (1998) indicates that applying an accessibility measure for jobs-housing balance may be more powerful than using a conventional measure since opportunities outside of the residential zone are weighted according to the impacts of distance. Accessibility balance considers not only the existing number of jobs and housing units in a zone but also the opportunities given in other areas according to the spatial distance decay. In the context of planning policy, the accessibility balance poses policy implications in that it has the ability to simulate future trends of different accessibility levels. For example, transportation projects or land use developments that affect or are affected by accessibility changes could be evaluated.

Another issue here is “jobs-housing balance for which type of workers”. As argued before, jobs-housing balance must be measured based on the disaggregated socio-economic groups, otherwise real jobs-housing balance for a particular group of workers (e.g. service workers) might be different from that of other groups of workers (e.g.
transportation workers, military workers). Even in “a perfectly balanced situation” where no outbound trips are expected, service workers may have to commute to external zones while transportation workers may not.

2.3 Accessibility

The definition of accessibility varies depending upon the types of interactions and traveling characteristics. Accessibility is often defined as the potential of opportunities for interaction (Hansen 1959), the degree of advantage to overcome spatial friction (Ingram 1971), or the potential for desired interaction (Handy 1994, Helling 1998). Accessibility is a spatial concept determined by the location of potential destinations as well as spatial barriers to reach those destinations. Accessibility reflects the magnitude and the character of activities in a given geographical area. A conventional accessibility measure can be described as follows (Hansen 1959):

\[ A_i = \sum_j W_j f(c_{ij}) \]  

(2.8)

where \( A_i = \) accessibility of zone \( i \) to all \( j \), \( W_j = \) opportunities at zone \( j \), \( c_{ij} = \) costs between zone \( i \) and \( j \), and \( f(c_{ij}) = \) spatial impedance function between zone \( i \) and \( j \)

Ingram (1971) clarifies his definition suggesting two measures: relative and integral accessibility. The relative accessibility refers to the connection between two locations and the integral accessibility considers the degree of interconnections with all other locations.
Levinson (1998) looks at accessibility as “a continuous variable measured by activities (e.g. jobs) available at a given distance from an origin (e.g. home), and discounting that number by the intervening travel time.” Handy (1993) explains accessibility at two geographic scales. Local accessibility is defined within a community and regional accessibility refers to the regional traveling. Handy emphasizes local accessibility in that policies improving local accessibility can reduce automobile dependency.

Accessibility has been a key indicator of land use, transportation planning, and urban policy. For the last couple of decades, researchers have used accessibility as their key measure to investigate people’s spatial behavior (Helling 1998, Levinson 1998, Shen 1998, Kwan 2000a, 2000b, Wang 2001, Horner 2002, Levine 2002). Without doubt, accessibility is central to transportation planning (Levine 2002) and the current debate about accessibility surrounds its relative importance compared to other factors (Badoe and Miller 2000). In land use and transportation interactions, accessibility has some advantages (Helling 1998) as a measure. Allowing the use of available transportation options, accessibility can be used as a density measure, as a potential, and as an outcome measure (Helling 1998). Potential accessibility addressed “potential or opportunity to travel to selected activities” and the outcome measure represents “the actual use and levels of satisfaction” (Helling 1998). The potential accessibility is more preferred since it may be applied for hypothesized scenarios to assess and forecast future impacts of accessibility on land use and urban form.
Accessibility has become a primary concern in recent transport planning. Advocates of accessibility planning argue that increasing accessibility should be a primary goal to save travel costs and to provide more options of reaching jobs (Cervero 1997, Levine 2002). In contrast, mobility planning emphasizes the reduction of congestion by improving road capacity and travel speed (Handy 1994). A comparison of accessibility planning and mobility planning is as follows:

<table>
<thead>
<tr>
<th>Mobility Planning</th>
<th>Accessibility Planning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Goal</td>
<td>Provision of more destination options</td>
</tr>
<tr>
<td>Improvement of mobility</td>
<td>Improvement of accessibility</td>
</tr>
<tr>
<td>Reduction of congestion</td>
<td></td>
</tr>
<tr>
<td>Supply</td>
<td>Demand</td>
</tr>
<tr>
<td>Means</td>
<td>Minimize travel</td>
</tr>
<tr>
<td>Increase car speed</td>
<td>Community</td>
</tr>
<tr>
<td>Scale</td>
<td>Minimum travel distance</td>
</tr>
<tr>
<td>Individual</td>
<td></td>
</tr>
<tr>
<td>Result</td>
<td></td>
</tr>
<tr>
<td>Longer commutes without congestion</td>
<td>Minimum travel distance</td>
</tr>
</tbody>
</table>

Source: Cervero (1997) and Levine (2002)

Table 2.1 A comparison of mobility planning and accessibility planning

Mobility planning policies focus on reducing congestion by building more highways, adding more lanes to urban road systems, and even posing congestion pricing to users in order to increase travel speed and subsequently alleviate congestion levels (Levine 2002). However, once the congestion level is alleviated, one might expect longer commutes, which, in turn, may result in higher social costs. Since the mobility planning is concerned about congestion levels, commuting efficiency may not be achieved. Handy (1994) emphasizes two advantages of accessibility over mobility as a planning goal. First, transportation policy and land use policy can be coupled by using accessibility concept.
For example, relative impacts of the transportation policy (increasing capacity of roads) on accessibility levels can be compared with those of the land use policy (increasing mixed land use). Second, Handy (1994) insists that the higher level of accessibility is “inherently” a good concept. Mobility-focused policies basically overlook the essential purpose of travel, that is, the access rather than the movement (Levine 2002). The core difference between these two concepts is that accessibility is derived from the demand for activities while mobility focuses on the ability of travel as an end itself (Handy 1994).

Accessibility contributes to lower social costs (Cervero 1997, Levine 2002). Shortening spatial separation between jobs and housing reduces commuting distance that in turn minimizes excess commuting. One question is whether mobility and accessibility are mutually exclusive. Answering this question may imply that mobility should be placed as a secondary concern once accessibility is promoted. An ideal situation is when one can have “increased accessibility in the form of proximity of desired destinations”, even if it does not enhance travel speed (Levine 2002). This statement suggests that the congestion may be reduced in the ideal stage where people travel shorter distances. However, the priority of policy goal is not on the congestion issue but on the accessibility in the form of proximity. Levine (2002) speaks that even the accessibility planning policies may not stop growing travel needs because of growing wealth and knowledge of people.
2.4 Diurnal shift of workers

Akkerman (2000) suggests a way to investigate the household choice of residence and workplace in an input-output framework. Based on the difference between daytime and nighttime population, Akkerman (2000) proposes two useful measures that address dynamic aspects of commuting. Population shift ratio (F) explains a switch of daytime population and nighttime population and commuting exchange ratio (G) calculates the ratio of outbound flows to the total daytime workers:

\[
F_l = \frac{\sum_{j} X_{lj}}{\sum_{l} X_{il}} \quad (2.9)
\]

\[
G_l = \frac{\sum_{j \neq i} X_{lj}}{\sum_{l} X_{il}} \quad (2.10)
\]

where

\[X_{lj} = \text{total number of outbound commuters from zone } l \text{ to } j\]
\[X_{il} = \text{total number of inbound commuters from zone } i \text{ to } l\]

When applied to the journey-to-work matrix, the population shift ratio (F) is the same measure of jobs-housing balance. The commuting exchange ratio (G) provides a useful way to look into the dynamic aspect of commuting. Even in the case of balance, a big “switch” of diurnal workers shift can disguise this balance. In addition, a G value implies intrazonal commuting flows by a simple relation as follows. Note that G values increase as the percentage of intrazonal commuters increases or that of outbound commuters decrease. Considering that the promotion of jobs-housing balance concerns about
removing unnecessary flows, maintaining high percentage of intrazonal commuters is important. This is consistent with a primary goal of jobs-housing balance policies that aims to be closer to the stage of minimum commuting distance, which has been a main topic in the literature (Horner 2002).

It is perceived that there is a relationship between worker shifts between day and night and jobs-housing balance. We have to consider a possibility of disguised balance due to different level of outbound or inbound commuting flows for each zone and more importantly for each group of workers. For example, even in a perfectly balanced situation at the aggregate, outbound or inbound flows may occur in some of workers who have sufficient number of jobs in their residential zone. Therefore, the diurnal aspect of workers movement should be added to explain more thorough investigation regarding the level of balances. This situation suggests a need for a more realistic job-housing balance measure or a multi-dimensional approach with the consideration of occupational types. In order to capture this, disaggregating journey-to-work flow is necessary.

2.5 Modifiable areal unit problem

Modifiable areal unit problem (MAUP) refers to the impacts of different scales and zoning schemes on the analysis results (Openshaw 1984, Openshaw and Taylor 1981). The MAUP is first recognized Gehlke and Biehl (1934) followed by Yule and Kendall (1950) who demonstrate that correlation coefficients could greatly vary according to the number and the size of areal units. The MAUP consists of two elements: scale problem
and unit definition problem or zoning problem (Openshaw 1984, Amrhein 1995, Marceau 1999). The scale problem refers to the variations in numerical results when zones are aggregated into larger and fewer geographical units (Openshaw 1984). For example, the levels of excess commuting percents are found to be lower when larger units are used in the analysis. Marceau (1999) explains the scale according to two different frameworks: absolute and relative frameworks. In the absolute framework, scale is operational since geographical space can be represented into practical and operational spatial units such as census units, traffic analysis zones, county, and any zoning system defined for a particular study. In the relative framework, scale is defined as a way to view and recognize the real world. Amrhein (1995) examines MAUP by aggregating data into three scales and finds that mean, variance, and correlation coefficients alter as data is aggregated into larger spatial units. The unit definition problem or zoning problem concerns about the error due to various combinations of zone systems and usually occurs when the different number of zones is used at the same scale (Openshaw 1984, Marceau 1999, Horner and Murray 2002).

The implications of the MAUP have been investigated in the excess commuting (Horner and Murray 2002) and in multivariate statistical analysis (Fotheringham and Wong 1991). However, there seems to be no solid answer regarding how to solve MAUP, since virtually all geographical studies including excess commuting research are scale dependent. In addition, when spatial data are aggregated for individuals in zones, the empirical results obtained from these aggregate data may be affected by the diverse configurations of zones. There is no guarantee of objective design of zoning systems.
because an optimal zoning system may not be the optimal for other zoning system (Openshaw 1984). Openshaw (1984) provides an idea arguing that the variation of the results can be thought of as another valuable information source about the spatial entities under study.

Fortunately, the advanced capabilities of computers and the widespread use of technologies such as geographic information systems (GIS) provide novel ways to address and experiment various spatial issues. GIS allows to predict and control the MAUP effects and to explain how geographic patterns and processes vary according to scales and zoning systems. Owing to GIS, it is now relatively easy to create multi-scale representations by incorporating and linking digital maps at different scales (Nyerges 1995). In addition, the integration of statistical and mathematical functions into GIS allows for dealing with scale as a generic issue. Unlike most of its predecessors, GIS technology has enhanced the ability of storing, transmitting, and processing a range of geographical information in a more relevant way (Bernhardsen 1999). GIS is an effective way to integrate various transport data, in particular, to conduct policy-related issues with different planning scenarios (Nyerges 1995, Miller and Shaw 2001). GIS can help to address a variety of issues in policy, planning, design, and operation of activities owing to its ability to handle a relatively large data set equipped with enhanced functional capabilities such as database management, spatial analysis for complex computation, and visualization of large amount of information. GIS enables us to apply general principles to the specific conditions of locations and to get a better sense of differentiated geographic patterns (Bernhardsen 1999). GIS are particularly beneficial for analyzing the
relationships between variables at different scales, and for assessing the impact of scale in modeling.

2.6 Transportation and land use

The study of the relationships between transportation and land use has been one of major subjects in the commuting literature. Since Hansen (1959) links the accessibility with the land use, researchers have investigated the impacts of density, mixed land use, accessibility, and neighborhood design on commuting behavior (Badoe and Miller 2000).

Some researchers hypothesize that the travel behavior is affected by land use patterns and consequently affects traffic congestion levels (Cervero 1989). More specifically, mixed land uses and compact developments reduce the reliance on the automobile travels (Cervero 1989 and 1996b, Kockelman 1997). Cervero (1989) compares commuting patterns in suburban employment centers in San Francisco Bay Area. It is hypothesized that land use would affect automobile-dependent travel behavior and consequently cause traffic congestion. He identifies six land use types such as office park, office center, larger mixed-use center, moderate-use center, sub-city, and larger corridor and investigates commuting patterns with these land use types. He finds that higher density and greater mixed-land use are positively related to non-automobile commuting. In his subsequent research using 1985 American Housing Survey, Cervero (1996b) finds that the mixed use of residential and commercial lands is associated with non-automobile

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1 This categorization is based on the empirical research in North America (Badoe and Miller, 2000)
travel within relatively short distance (300 feet from one’s residence). In general though, residential densities are more influential on the mode choice than land-use mixing except for walking and bicycle travels. In the same line with Cervero’s research, Kockelman (1997) explores the relative influence of urban form on the household VKT, automobile ownership, and the mode choice for San Francisco Bay Area. Urban form is defined by several measures: density, accessibility, land-use balance, and land use mix. She finds that accessibility to opportunities is strongly related to all three of travel behavior. Land use balance and mixing are significant on VKT, but not on the personal vehicle choice. Population and job densities show significant impacts only on the vehicle ownership.

One of the most frequently cited studies on the relationship between density and travel behavior is a study by Newman and Kenworthy (1989). Gasoline consumption per capita is compared among 32 cities including 10 US cities. While US cities have low population and job densities, they appear to have higher energy consumption levels than non-US cities. Given the empirical results, Newman and Kenworthy suggest that increasing urban density should be considered in policies to save fuel consumptions. Levinson and Kumar (1997) suggest that density may be used as a substitute for city size. They analyze 38 US cities to investigate the effects of residential density on the travel behavior. Their regression analysis shows that distance and time are negatively related with density while auto travel time seems to have threshold density at 10,000 people per square mile. Once density exceeds 10,000, auto travel time shows positive associations with density. They argue that beyond a certain density level automobile travel is less attractive because of worse traffic congestion. Miller and Ibrahim (1998) investigate the changes of vehicles
kilometers traveled (VKT) in Toronto area with respect to the distance from CBD and employment centers. They find that Vehicle kilometers traveled (VKT) per worker appear to increase as distance increases from CBD or larger employment zones.

A common problem in the past is the lack of considering interacting factors between travel behavior and land use. Badoe and Miller (2000) provide a thorough review on the empirical studies of the transportation-land use interaction. Their review emphasizes the importance of integrated transportation-land use models with elaborated methodological frameworks along with the quality of data. On the same line, summarizing existing theories and empirical findings, Giuliano (1989) suggests that temporal elements and non-work activities should be included in models. In this sense, accessibility and diurnal shift of workers may provide an extended way to investigate commuting dynamics in a diurnal cycle. So the transportation and land use connection in a broad sense can be addressed because transportation has at least indirect impacts on land use pattern (Giuliano 1989).

2.7 Modeling framework

Residential location/trip distribution models address the question of matching a fixed place of work to a variable trip origin by using an attraction constrained gravity model. The interesting question here is whether both the fixed locations of residence and employment match, and at the same time determine how those levels of spatially aggregate locations can be produced by varying interchanges between origins and
destinations. There are certain feasibility conditions that must be satisfied in matching a person earning a particular level of income with a neighborhood that has appropriately priced housing.\(^2\) Any feasible solution to the present trip distribution table is just one of a multitude of potential solutions. There are of course extreme values of the trip distribution table: one well-known example is where the transportation problem is solved to match the supply and demand in the most efficient way (produced by the solution to an appropriate linear program). In addition, for benchmarking purposes, we can ask the most inefficient way of matching so as to produce a comparative scale (Horner, 2002). When the linear program (LP) is solved for the aggregate total flow in this way, it is explicitly assumed that any worker at zone \(i\) can fill any job at zone \(j\). This solution ignores the typology of the workers and their spatial distribution by worker and employment type. Another method is to use entropy-maximizing models to complete the body of the interaction table in a way that is consistent with marginal totals, while remaining maximally noncommittal with respect to missing information. Other work derives from taking combinations of extreme distributions and is a sufficiently different point of departure as to be outside the scope of our current analysis (reviewed in Thorsen et al. 1999, Ubøe 2004).

### 2.7.1 Spatial interaction models

Spatial interaction models estimate the most probable distribution of interactions between places based on the given information (Fotheringham and O’Kelly 1989). Spatial

---

\(^2\) See for example the variants of the Herbert-Stevens model and the Alonso budgetary constrained utility maximization problem reported in Wilson (1970).
interaction models are detailed in Wilson (1967) and have been widely employed for a variety of research, such as migration studies, retail analysis and commuting behavior (Fotheringham and O’Kelly 1989) where estimates of various interaction flows are needed. For trip distribution estimation, spatial interaction models produce balancing factors that have been used as accessibility measures (Cesario 1977, Horner 2004). This section primarily focuses on the implications of balancing factors obtained from the doubly constrained spatial interaction model (SI model). The doubly constrained model is as follows:

\[ T_{ij} = A_i O_i B_j D_j \exp(-\beta c_{ij}) \]  \hspace{1cm} (2.11)

\[ A_i = \left[ \sum_j B_j D_j \exp(-\beta c_{ij}) \right]^{-1} \]  \hspace{1cm} (2.12)

\[ B_j = \left[ \sum_i A_i O_i \exp(-\beta c_{ij}) \right]^{-1} \]  \hspace{1cm} (2.13)

where \( A_i \) and \( B_j \) ensure that

\[ \sum_j T_{ij} = O_i \]  \hspace{1cm} (2.14)

\[ \sum_i T_{ij} = D_j \]  \hspace{1cm} (2.15)

respectively.

where, \( i \) and \( j \) = zone index, \( T \) = total number of work trips, \( T_{ij} \) = predicted interactions between \( i \) and \( j \), \( O_i \) = number of workers in zone \( i \), \( D_j \) = number of jobs in zone \( j \),
$A_i$ and $B_j$ = balancing factors for rows and columns, respectively, and $c_{ij}$ = travel costs between $i$ and $j$

The doubly constrained SI model provides “normalizing” or “balancing” factors (2.12 and 2.13) by which accessibility issue can be addressed (Cesario 1977). Cesario (1977) makes a statement of using balancing factors as accessibility measures as follows:

“the terms ($1/A_i$) and ($1/B_j$) are in fact measures of accessibility (and not merely “related” to accessibility as Wilson stated). Specifically, the terms ($1/A_i$) measures the accessibility of destinations with respect to origin $i$ and ($1/B_j$) measures the accessibility of origins with respect to destination $j$.”

Row and column balancing factors are origin ($A_i$) and destination ($B_j$) specific, so that flows are predicted as best as possible to the observed flows. According to Cesario, origin accessibility scores can be obtained from the inverse of row balancing factor (2.16) and destination accessibility scores are similarly obtained from the inverse of column balancing factors (2.17). Recognize that the denominator of $A_i$ has a similar form compared to the accessibility measure proposed by Hansen (1959). The inverse of $A_i$ explains the total accessibility from origin $i$ (e.g. home locations) to reach opportunities (e.g. job locations) at all $j$ by the distance decay function. The inverse of column balancing factor, $B_j$, is indicative of the ability of destination $j$ (e.g. job locations) to attract workers from zone $i$. 

34
Another usefulness of balancing factors (not inverse) is the ability to detect how many workers emanate from their residential areas, “emissiveness”, and which areas are attracting those workers, “attractiveness” (Cesario 1977). These two measure actually screen zones that have low accessibility but produce or attract a large volume of workers. Multiplying balancing factors by $O_i$ and $D_j$ calculates emissiveness and attractiveness, respectively.

\[
Emissiveness = A_i O_i = \frac{O_i}{\sum_j B_j D_j \exp(-\beta c_{ij})}
\]  

(2.18)

\[
Attractiveness = B_j D_j = \frac{D_j}{\sum_i A_i O_i \exp(-\beta c_{ij})}
\]  

(2.19)

2.7.2 Transportation problem

Among various optimization techniques, transportation problem (TP) has been applied for commuting analysis especially in excess commuting literature as a way to obtain the best possible pattern of commuting (White 1988, Small and Song 1992, Horner 2002). The generic transportation problem is as follows.
\[
\text{MINIMIZE} \quad \frac{1}{K} \sum_i \sum_j T_{ij} c_{ij} \quad (2.20)
\]

subject to
\[
\sum_j T_{ij} = D_j \quad \forall j \quad (2.21)
\]
\[
\sum_i T_{ij} = O_i \quad \forall i \quad (2.22)
\]
\[
T_{ij} \geq 0 \quad \forall i, j \quad (2.23)
\]

where \(i\) = residential zones, \(j\) = employment zones, \(O_i\) = number of workers residing in zone \(i\), \(D_j\) = number of employees in zone \(j\), \(c_{ij}\) = travel costs between zone \(i\) and zone \(j\), \(T_{ij}\) = commuting flows from zone \(i\) to zone \(j\), and \(K\) = total number of commuters.

The objective function (2.20) is to find the optimal commuting pattern by minimizing average travel costs. Constraint (2.21) makes sure that all employment demands should be satisfied. Constraint (2.22) ensures that the supply of workers should not exceed the number of workers residing in each zone. Decision variables are non-negative in (2.23). \(K\) is the total number of commuters for the entire study area. In spite of a wide usage of TP, we need a caution in terms of jobs–housing balance. The ratio of jobs to workers for the observed flow always results in 1 system-wise in a conventional way. This justifies a need for accessibility balance as a jobs-housing measure in a modeling framework.
Erlander (1976) extends the TP formulation by adding an entropy constraint (2.27). Assuming entropy as a surrogate for an accessibility measure, Erlander’s model forces to maintain a certain accessibility level.

\[
\begin{align*}
\text{MINIMIZE} & \quad \frac{1}{T} \sum_i \sum_j \mathcal{T}_{ij} c_{ij} \\
\text{subject to} & \quad \sum_j \mathcal{T}_{ij} = D_j \quad \forall j \quad (2.25) \\
& \quad \sum_j \mathcal{T}_{ij} = O_i \quad \forall i \quad (2.26) \\
& \quad H = -\sum_i \sum_j \frac{\mathcal{T}_{ij}}{T} \log \frac{\mathcal{T}_{ij}}{T} \geq H_0 \quad \forall i, j \quad (2.27) \\
& \quad \mathcal{T}_{ij} \geq 0 \quad \forall i, j \quad (2.28)
\end{align*}
\]

where, \( H \) = entropy measure and \( H_0 \) = minimum entropy.

Erlander’s model is unique in that it incorporates the objective function of entropy maximization into TP as a constraint. The optimal solution is obtained while the minimum entropy is ensured. Still, it is vague to address jobs-housing balance or urban efficiency in an intuitive way since the entropy measure doesn’t tell much about opportunities that people can choose from.
Recently, an extended TP is formulated to address excess commuting and jobs-housing balance (Horner and Murray 2002). Horner and Murray (2002) add relocation components while jobs and housing changes are simulated.

$$\text{Minimize } W_i \frac{1}{K} \sum_i \sum_j C_{ij} x_{ij} + W_\theta \frac{1}{K} \sum_i (\theta_i^+ + \theta_i^-) + W_\beta \frac{1}{K} \sum_j (\beta_j^+ + \beta_j^-)$$

subject to,

$$\sum_j x_{ij} = O_i + \theta_i^+ - \theta_i^- \quad \forall i$$

(2.30)

$$\sum_i x_{ij} = D_j + \beta_j^+ - \beta_j^- \quad \forall j$$

(2.31)

$$\sum_i (\theta_i^+ - \theta_i^-) = 0 \quad \forall i$$

(2.32)

$$\sum_j (\beta_j^+ - \beta_j^-) = 0 \quad \forall j$$

(2.33)

$$x_{ij}, \theta_i^+, \theta_i^-, \beta_j^+, \beta_j^- \geq 0 \quad \forall i, j$$

(2.34)

where,

$W_i =$ Weight on the commuting assignment

$W_\theta =$ Weight on the reallocation of workers

$W_\beta =$ Weight on the reallocation of jobs

$\theta_i^+$ = number of workers added to the $i$th zone

$\theta_i^-$ = number of workers subtracted from the $i$th zone

$\beta_j^+$ = number of jobs added to the $j$th zone

$\beta_j^-$ = number of jobs subtracted from the $j$th zone

$\Omega =$ a significantly large number
Their model is valuable in that jobs and workers are relocated and the reduction of excess commuting is investigated at the same time. Their multi–objective approach enables the model to simulate system-wise pattern for excess commuting reduction according to relocation effects. However, Horner and Murray (2003) treat the workers as homogeneous without breaking down the numbers into detailed categories. Deciding the desirable degree of reallocation of workers or jobs without differentiating worker and jobs types may result in limited explanation. From this simple question, one might need to have information of possible composition of workers in a zone relocate jobs and workers under a specific policy scenario. Recognizing the value of the model proposed by Horner and Murray, this research will address this issue later on in the chapter 6.
CHAPTER 3 STUDY AREA AND DATA

3.1 The tri-state area

This dissertation focuses on the county level analysis of Indiana, Kentucky, and Ohio. The tri-state area contains 300 counties; 92 counties in Indiana, 120 counties in Kentucky, and 88 counties in Ohio (Table 3.1). The total number of resident workers has grown from 8.6 million in 1990 to 9.8 million in 2000. Over the ten-year period between 1990 and 2000, the tri-state has gained an 11% increase in the work force, slightly smaller than the national average of 11.5% (US Census Bureau, 2004). Kentucky has increased 13.9% of the work force followed by Indiana and Ohio (see Table 3.1).

<table>
<thead>
<tr>
<th>State</th>
<th>Number of counties</th>
<th>Total number of resident workers*</th>
<th>Percent increase 1990-2000 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1990</td>
<td>2000</td>
</tr>
<tr>
<td>Indiana</td>
<td>92</td>
<td>2,462,256</td>
<td>2,763,709</td>
</tr>
<tr>
<td>Kentucky</td>
<td>120</td>
<td>1,461,460</td>
<td>1,663,957</td>
</tr>
<tr>
<td>Ohio</td>
<td>88</td>
<td>4,733,951</td>
<td>5,183,013</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>300</strong></td>
<td><strong>8,657,667</strong></td>
<td><strong>9,810,476</strong></td>
</tr>
</tbody>
</table>

* Workers both living and working in their state

Table 3.1 Study area
Figure 3.1 Metropolitan statistical areas in the tri-state (2000)
Figure 3.1 is a regional map highlighting all metropolitan statistical areas (MSAs) defined in 2000 census. Each MSA embraces a set of counties defined by census. The tri-state area is a highly automobile-oriented region in that three states are all ranked within the top ten states in the percent of workers who drive alone (US Census Bureau 2004). Indiana shows 81.8%, Kentucky 80.2%, and Ohio 82.8%, while the national average is 75.7%. Among the top 10 MSAs for the highest percent in the category, 5 MSAs are located in the tri-state area: Youngstown-Warren OH (86.2%), Canton-Massillon OH (86.0%), Steubenville-Weirton, OH-WV (85.3%), Owensboro KY (85.1%), and Evansville-Henderson KY-IN (85.0%).

The tri-state accommodates several major large metropolitan statistical areas (MSAs) such as Indianapolis, Cleveland, Cincinnati, Columbus, and Louisville MSAs. Cincinnati MSA, in particular, lies at the intersection of three states and consists of counties that belong to all three states. When one looks at Ohio portions only, interactions occurring with Kentucky or Indiana portions of Cincinnati MSA may be misinterpreted, and as a result, the significant volume of worker flow between Ohio and Kentucky or Ohio and Indiana may be ignored. Noting this issue, this dissertation explicitly captures state-to-state worker flows that occur in Cincinnati and Louisville MSAs. By doing so, inter-state workers who travel across states in the tri-state are captured.
3.2 Census Transportation Planning Package

The primary data source is the Census Transportation Planning Package (CTPP) published by the US Bureau of Transportation Statistics (BTS). CTPP is a set of tabulations of census data and consists of three parts: part 1, 2, and 3.

Part 1 is tabulated by the place of residence and provides residential county data. Part 2 is based on the place of work and provides employment data. Part 3 is tabulated by the distribution of worker’s residence and workplace (BTS 1990). Part 3, in particular, directly provides a journey-to-work flow matrix that can be directly extracted using a TransCAD planning utility. At the county level, the Census Bureau provides county-to-county worker flow files that are compiled from Census responses to the long-form (sample) questions. A caution is required for each part of CTPP due to the different characteristics of the recording universe. For instance, the number of total workers in part 1 does not match that of part 2 or part 3. The number of workers in part 1 is only for workers who live in the region regardless of the location of their workplaces. Part 2 counts workers who work in the region no matter where they live. Part 3 or county-to-county worker flow is restricted to resident workers who both live and work in the region. For the same region, total sum of workers of the aggregate flow matrix is always smaller than total sum in part 1 and in part 2.

CTPP has two elements by geographic scale: statewide element and urban element. Statewide element is county level data aggregated by each state and urban element is based on the traffic analysis zone (TAZ) or optional census geography defined by Metropolitan Planning Organizations (MPOs) for each MSA. This dissertation uses statewide element focusing on county level analysis.
3.3 Occupational classification in CTPP

One of issues in CTPP data is inconsistency of occupational classifications between 1990 and 2000. This is due to the changes in the occupational classification systems used in 1990 Census and 2000 Census (US Census Bureau 2003). The 1990 Census adopts the standard occupational classification (SOC), originally applied for the 1980 Census, and categorizes 14 occupational groups. The 2000 SOC is a revamped version of 1980 SOC since the entire structure of occupational classification is rearranged. Major revisions in SOC have been made to reflect dramatic changes in the labor force over the past two decades and to identify current occupational structure in the US. As a result of these changes, the 2000 SOC classifies 24 occupational groups. However, many 2000 occupational categories are not comparable to similar categories and groups in 1990 or earlier Censuses (US Census Bureau 2003).

In order to conduct a comparative analysis of 1990 and 2000, a consistent classification system of occupation that can be applicable for both census years is needed. One of the ways is to aggregate 1990 and 2000 occupational groups that are similar in their characteristics in both years. Based on the examination of the major occupational groups in 1990 and 2000, total 6 aggregated occupational groups are created (Table 3.2). Those 6 occupations are: (1) managerial and professional occupations, (2) sales occupations, (3) service occupations, (4) farming, forestry, and fishing occupations, (5) transportation and production occupations, and (6) military occupations. This rearrangement of groups is not perfect but is consistent with the classification appearing in Census Report (2003b). See Table 3.2 for further details. Table 3.3 summarizes occupational composition and its
change over the ten-year period. In general, more than 80% of the tri-state workers are in
groups of managerial and professional occupations, service occupations, and
transportation and production occupations. Indiana and Kentucky show the highest
percent in transportation and production occupations while Ohio has the highest percent
in managerial and professional occupations. Interestingly, the highest increase of workers
in Indiana and Kentucky is found in managerial and professional workers (27.1% and
34.4%, respectively), while the number of service workers in Ohio has increased by
21.8%. Another noticeable change is the dramatic decline of workforce in farming,
forestry, and fishing occupations, which suggests a rapid transition to more advanced
economic structure. Since this dissertation deals with occupational variations in excess
commuting, jobs-housing balance, and accessibility taking a comparative point of view,
obtaining occupational data and making it consistent are central steps for analyses in the
later chapters.
<table>
<thead>
<tr>
<th>New Occupational Groups (6 groups)</th>
<th>CTPP 1990 (14 groups)</th>
<th>CTPP 2000 (24 groups)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Managerial and professional</td>
<td>Executive, administrative, and managerial</td>
<td>Management</td>
</tr>
<tr>
<td></td>
<td>Professional specialty</td>
<td>Farmers and farm managers</td>
</tr>
<tr>
<td></td>
<td>Technicians and related support</td>
<td>Business and financial operations specialists</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Computer and mathematical</td>
</tr>
<tr>
<td>2 Sales</td>
<td>Sales</td>
<td>Sales and related occupations</td>
</tr>
<tr>
<td></td>
<td>Administrative support (including clerical)</td>
<td>Office and administrative support</td>
</tr>
<tr>
<td>3 Service</td>
<td>Private household</td>
<td>Healthcare support</td>
</tr>
<tr>
<td></td>
<td>Protective service</td>
<td>Protective service</td>
</tr>
<tr>
<td></td>
<td>Service (except protective and household)</td>
<td>Food preparation and serving related</td>
</tr>
<tr>
<td>4 Farming, fishing, and forestry</td>
<td>Farming, fishing, and forestry</td>
<td>Building, grounds cleaning, maintenance</td>
</tr>
<tr>
<td>5 Transportation and production</td>
<td>Transportation and material moving</td>
<td>Personal care and service</td>
</tr>
<tr>
<td></td>
<td>Precision production, craft, repair</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Machine operators, assemblers, inspectors</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Handlers, equipment cleaners, helpers, laborers</td>
<td></td>
</tr>
<tr>
<td>6 Military</td>
<td>Armed forces</td>
<td>Armed Forces</td>
</tr>
</tbody>
</table>

Table 3.2 Occupational classification systems
<table>
<thead>
<tr>
<th>Occupation by state</th>
<th>Composition (%)</th>
<th>Increase (%) (1990-2000)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1990</td>
<td>2000</td>
</tr>
<tr>
<td>Indiana</td>
<td>100.0</td>
<td>100.0</td>
</tr>
<tr>
<td>Managerial and professional</td>
<td>25.5</td>
<td>28.9</td>
</tr>
<tr>
<td>Sales</td>
<td>26.3</td>
<td>25.3</td>
</tr>
<tr>
<td>Service</td>
<td>13.1</td>
<td>14.1</td>
</tr>
<tr>
<td>Farming, forestry, fishing</td>
<td>2.3</td>
<td>0.4</td>
</tr>
<tr>
<td>Transportation and production</td>
<td>32.4</td>
<td>31.3</td>
</tr>
<tr>
<td>Military</td>
<td>0.4</td>
<td>0.0</td>
</tr>
<tr>
<td>Kentucky</td>
<td>100.0</td>
<td>100.0</td>
</tr>
<tr>
<td>Managerial and professional</td>
<td>24.3</td>
<td>28.7</td>
</tr>
<tr>
<td>Sales</td>
<td>25.4</td>
<td>25.3</td>
</tr>
<tr>
<td>Service</td>
<td>12.8</td>
<td>14.1</td>
</tr>
<tr>
<td>Farming, forestry, fishing</td>
<td>3.6</td>
<td>0.9</td>
</tr>
<tr>
<td>Transportation and production</td>
<td>32.0</td>
<td>30.5</td>
</tr>
<tr>
<td>Military</td>
<td>1.9</td>
<td>0.5</td>
</tr>
<tr>
<td>Ohio</td>
<td>100.0</td>
<td>100.0</td>
</tr>
<tr>
<td>Managerial and professional</td>
<td>28.5</td>
<td>31.2</td>
</tr>
<tr>
<td>Sales</td>
<td>27.2</td>
<td>26.4</td>
</tr>
<tr>
<td>Service</td>
<td>13.0</td>
<td>14.5</td>
</tr>
<tr>
<td>Farming, forestry, fishing</td>
<td>1.7</td>
<td>0.3</td>
</tr>
<tr>
<td>Transportation and production</td>
<td>29.2</td>
<td>27.6</td>
</tr>
<tr>
<td>Military</td>
<td>0.4</td>
<td>0.0</td>
</tr>
</tbody>
</table>

Note: Data from CTPP part 1 according to worker’s residential location

Table 3.3 Occupational composition and changes
3.4 Consistency in geographic units in CTPP

Another issue in CTPP data from a comparative standpoint is whether a researcher can obtain consistent geographic units for the same area. For a researcher to investigate temporal trends of excess commuting, it is critical to have the same geographical unit both time periods. Many MSAs defined by census contains different geographical units, for instance, traffic analysis zones (TAZs) in 1990 and census block groups in 2000. Along with occupational discrepancies, this makes a comparative analysis impossible since, as an example, the cost matrix calculated based on the TAZ configuration is not the same with the cost matrix from census block group units.

In addition, due to the urban sprawl trend that causes growing levels of interactions, many MSAs’ boundaries have been redefined (US Census Bureau 1998 and 1999). Adjacent counties showing a high degree of economic and social integration with an existing MSA can be included to the MSA. Economic and social integration is measured by county-based commuting patterns and each MSA is defined entirely by county borders. In the tri-state area, Cincinnati PMSA has added 5 counties to 2000 definition: Ohio (IN), Brown (OH), Gallatin (KY), Grant (KY), and Pendleton (KY) counties. Cleveland PMSA has also added Ashtabula county (OH) while Columbus MSA has dropped Union county and now consists of 6 counties (Delaware, Fairfield, Franklin, Licking, Madison, and Pickaway). Indianapolis MSA has no change in its county borders and Louisville MSA has added Scott county (IN) but dropped Shelby county (KY) from the 2000 definition.
Noting these issues, this dissertation focuses on county level analysis for two reasons. First, the county configuration has not been changed so that the consistency in terms of geographical unit is maintained. Second, counties are not affected by changing MSA definitions, rather, it may be possible to identify and possibly predict future trends of the county level interactions that might be reflected in the next 2010 census.
<table>
<thead>
<tr>
<th>MSA</th>
<th>1990 definition</th>
<th>Changes in 2000 definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cincinnati PMSA (OH-IN-KY)</td>
<td>*Hamilton (OH)</td>
<td>Counties included:</td>
</tr>
<tr>
<td></td>
<td>Dearborn (IN)</td>
<td>Ohio (IN)</td>
</tr>
<tr>
<td></td>
<td>Boone (KY)</td>
<td>Gallatin (KY)</td>
</tr>
<tr>
<td></td>
<td>Campbell (KY)</td>
<td>Grant (KY)</td>
</tr>
<tr>
<td></td>
<td>Kenton (KY)</td>
<td>Pendleton (KY)</td>
</tr>
<tr>
<td></td>
<td>Clermont (OH)</td>
<td>Brown (OH)</td>
</tr>
<tr>
<td></td>
<td>Warren (OH)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Counties included:</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Ashtabula (OH)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cleveland-Lorain-Elyria PMSA (OH)</td>
<td>*Cuyahoga (OH)</td>
<td>Counties included:</td>
</tr>
<tr>
<td></td>
<td>Geauga (OH)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Lake (OH)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Medina (OH)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Lorain (OH)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Counties included:</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Ashtabula (OH)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Columbus (OH)</td>
<td>*Franklin (OH)</td>
<td>Counties excluded:</td>
</tr>
<tr>
<td></td>
<td>Delaware (OH)</td>
<td>Union (OH)</td>
</tr>
<tr>
<td></td>
<td>Fairfield (OH)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Licking (OH)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Madison (OH)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Pickaway (OH)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Union (OH)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Counties excluded:</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Union (OH)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indianapolis (IN)</td>
<td>*Marion (IN)</td>
<td>Same as 1990</td>
</tr>
<tr>
<td></td>
<td>Boone (IN)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Hamilton (IN)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Hancock (IN)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Hendricks (IN)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Johnson (IN)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Madison (IN)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Morgan (IN)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Shelby (IN)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Louisville (KY-IN)</td>
<td>*Jefferson (KY)</td>
<td>Counties included:</td>
</tr>
<tr>
<td></td>
<td>Clark (IN)</td>
<td>Scott (IN)</td>
</tr>
<tr>
<td></td>
<td>Floyd (IN)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Harrison (IN)</td>
<td>Counties excluded:</td>
</tr>
<tr>
<td></td>
<td>Bullitt (KY)</td>
<td>Shelby (KY)</td>
</tr>
<tr>
<td></td>
<td>Oldham (KY)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Shelby (KY)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Major urban counties
Source: US Census Bureau (www.census.gov)

Table 3.4 Definition changes in major tri-state MSAs
CHAPTER 4  A DISAGGREGATE ANALYSIS OF EXCESS COMMUTING AND JOBS-HOUSING BALANCE BY OCCUPATION

Much of the analysis to date on the topic of excess commuting and jobs-housing balance deals with total commuting flow, undifferentiated with respect to worker and job characteristics. Undifferentiating worker types may yield misleading results in measuring excess commuting and jobs-housing balance because there is no guarantee that all workers are homogeneous. This chapter explicitly addresses the disaggregation issue in terms of job and worker heterogeneity by estimating trip distribution for each occupation. Such details are incorporated into the analysis of excess commuting and jobs-housing balance. The objectives of this chapter are: (1) to predict actual commute lengths by type of occupation, (2) to measure theoretical minimum commutes by type of occupation, and (3) to verify variations in excess commuting and jobs-housing balance by type of occupation. A set of disaggregated trip distribution models are presented, corresponding to objectives (1) and (2), respectively. Models are applied for the tri-state area containing 300 counties in Indiana, Kentucky, and Ohio both in 1990 and 2000 data.

4 Portions of chapter 4 appear in a research paper accepted for publication in *Environment and Planning A*, coauthored with Dr. Morton E. O'Kelly.
4.1 Data preparation

Four matrices are prepared for disaggregating journey-to-work data: aggregate journey-to-work flow matrix (X), cost matrix (Y), residential location data by worker type (S), and employment location data by occupation (D). Total worker flow, X, can be directly extracted from the journey-to-work flow in county-to-county worker flow files that are comparable to the Census Transportation Planning Package (CTPP) part 3. The cost matrix, Y, is calculated using Euclidean distances between zonal centroids. Note that congestion is not taken into account in the cost matrix. Both X and Y have the same number of origins and destinations \((i, j = 1, \ldots, n+1)\). Worker typology matrices by origin (S) and by destination (D) are obtained from CTPP part 1 and part 2, respectively.

In this dissertation, the following notation will be used.

\(i\) = index of trip origin

\(j\) = index of trip destination

\(k\) = index of occupational type

\(S_i\) = total number of workers departing from zone \(i\)

\(S_{ik}\) = number of workers in group \(k\) departing from zone \(i\)

\(D_j\) = total number of workers ending in zone \(j\)

\(D_{jk}\) = number of workers in group \(k\) ending in zone \(j\)

\(X_{ij}\) = total number of workers commuting from zone \(i\) to \(j\)

\(X_{ijk}\) = number of workers in group \(k\) commuting from zone \(i\) to \(j\)
4.1.1 Extended journey-to-work flow matrix (X)

Total worker flow, \( X \), is directly extracted from the journey-to-work flow in Census Transportation Planning Package (CTPP) part 3. Spatial interaction models require balanced totals for residences (origins) and workplaces (destinations). However, since total sums of workers from CTPP part 1, 2, and 3 do not match, we now propose a novel way to incorporate information from all three CTPP parts into a balanced origin-destination (O-D) matrix format (see Figure 4.1). This extended O-D matrix is used as an input to a trip distribution model and a linear program presented in the later sections.

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>…</th>
<th>…</th>
<th>…</th>
<th>( j )</th>
<th>…</th>
<th>…</th>
<th>8</th>
<th>9</th>
<th>( S_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( X_{11} )</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>( X_{18} )</td>
<td>( X_{19} )</td>
<td>( S_1 )</td>
</tr>
<tr>
<td>( i )</td>
<td>:</td>
<td>:</td>
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<td>:</td>
<td>:</td>
<td>( X_{ij} )</td>
<td>:</td>
<td>:</td>
<td>:</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>( X_{81} )</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>( X_{88} )</td>
<td>:</td>
<td>( S_8 )</td>
</tr>
<tr>
<td>9</td>
<td>( X_{91} )</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>( X_{99} )</td>
<td>( S_9 )</td>
<td></td>
</tr>
<tr>
<td>( D_j )</td>
<td>( D_1 )</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>( D_8 )</td>
<td>( D_9 )</td>
<td></td>
</tr>
</tbody>
</table>

*Figure 4.1 Extended flow matrix (8x8 example)*
An example in figure 4.1 initially has 8 origins and destinations as shown in the inner rectangle. The reason for the discrepancy in total flow is now clear; if we have the total number of workers residing in zone $i$, a selection of a particular number of destinations may not encompass all the places to which those trips are made: thus $S_i > \sum_j^n X_{ij}$. (Recall $S$ and $X$ come from different data sets.) Including one added external dummy destination, (the $9^{th}$ column), can reconcile the sum of $X$ and $S$. Similarly, one external dummy origin, (the $9^{th}$ row), is added to reconcile the sum of $X$ and $D$. The new extended matrix now has 9 origins and destinations, which makes the sums of matrices balance, as seen in the bigger rectangle in this example ($\sum_i^{n+1} S_i = \sum_j^{n+1} D_j = \sum_j^{n+1} \sum_i^{n+1} X_{ij}$). Each cell value in the external column ($9^{th}$ column) is the difference between the row sum of part 1 and that of part 3, such that, $X_{9i} = S_i - \sum_{j=1}^8 X_{ij}$. Similarly, each cell value in the external row ($9^{th}$ row) is the difference between the column sum of part 2 and that of part 3 such that, $X_{9j} = D_j - \sum_{i=1}^8 X_{ij}$. By doing so, the extended O-D matrix (9x9 matrix) is balanced and the following disaggregated conditions are satisfied:

\[
\sum_j^{n+1} X_{ijk} = S_{ik} \quad \forall k, i = 1, \ldots, n + 1 \quad (4.1)
\]

\[
\sum_i^{n+1} X_{ijk} = D_{jk} \quad \forall k, j = 1, \ldots, n + 1 \quad (4.2)
\]

\[
\sum_k^K S_{ik} = S_i \quad \forall i = 1, \ldots, n + 1 \quad (4.3)
\]
\[ \sum_{k}^{K} D_{jk} = D_{j} \quad \forall j = 1, \ldots, n + 1 \] (4.4)

Conditions (4.1) and (4.2) are obtained from CTPP part 1 and 2, respectively. Both conditions (4.3) and (4.4) are obtained from CTPP part 3.

### 4.1.2 Distance matrix (Y)

The distance matrix (Y) is calculated using Euclidean distances between zonal centroids. An arbitrary large value is given to the external row and column. Since the initial calculation of Y generated zero diagonal values \( y_{ii} = 0 \), diagonal values are replaced by non-zero values using the following equation (4.5) suggested in Frost et al. (1998).

\[ y_{ii} = \sqrt{\frac{R_i}{\pi}} \] (4.5)

where \( y_{ii} \) = intrazonal distance of zone \( i \), and \( R_i \) = the area of zone \( i \). It is assumed that a zone has a circular shape and then the intrazonal distance \( y_{ii} \) can be calculated as a radius of a zone \( i \) (Frost et al. 1998, Horner 2002). Once non-zero \( y_{ii} \) is given to every zone, it should be examined whether every \( y_{ii} \) is the actual minimum for each row. Due to the irregular shapes of zones (e.g. county, TAZ), some \( y_{ii} \) may not be the actual minimum distance. To resolve this, the following transformation has been applied.
\[ Y_{ii} = \frac{y_{ii}^{Min}}{y_{ii}} \times y_{ii}^{Min} \]  

(4.6)

where \( y_{ii}^{Min} \) = the minimum of row \( i \), \( y_{ii} \) = old intrazonal distance of zone \( i \), and \( Y_{ii} \) = new intrazonal distance of zone \( i \). All intrazonal distances are now the actual row minimums.

If \( y_{ii} \) (an old value) is the minimum in its row, we hold the value. However, if \( y_{ii} \) is not the row minimum, \( y_{ii} \) is adjusted by calculating \( Y_{ii} \), which makes \( y_{ii} \) lower than \( y_{ii}^{Min} \). These steps ensure that all intrazonal distances are true minimum values of each row guaranteeing that the intrazonal distance is not longer than other interzonal distances.

Otherwise, workers commuting to other zones may travel shorter than those commuting in their residential zones.

4.1.3 Worker typology matrices (S and D)

Worker typology matrices by origin (S) and by destination (D) are obtained from CTPP part 1 and part 2, respectively. Two more matrices are constructed in which detailed information of worker typology is presented. First, S contains the number of workers in origin \( i \), by occupation \( k \) (\( S_{ik} \)), obtained from CTPP part 1. Second, D, extracted from CTPP part 2, presents the number of workers in destination \( j \), by occupation \( k \) (\( D_{jk} \)). Sums of S and D are explicitly addressed in the extended O-D matrix as row sums and column sums, respectively (see figure 1). Due to the inconsistency of occupational groups between 1990 (14 occupations) and 2000 (24 occupations), occupational groups are reaggregated to 6 larger groups: (1) managerial and professional occupations, (2) sales
occupations, (3) service occupations, (4) farming, forestry, and fishing occupations, (5) transportation and production occupations, and (6) military occupations.

4.2 Estimation of journey-to-work flow by type of occupation

In this section, two disaggregation models are presented. First, the information-minimizing model disaggregating journey-to-work data is developed to predict average actual commutes for each occupation. Second, a disaggregated version of a linear program is developed to estimate theoretical minimum commutes. Both models produce 6 journey-to-work flow patterns, one for each type of occupation ($X_{ijk}$), disaggregated from the total worker flow ($X_{ij}$). The core idea is to estimate unknown $X_{ijk}$ values with controls for exogenous total worker flow.

Suppose that there is a detailed data set of the number of workers in type $k$ residing in zone $i$; ($S_{ik}$); the number of employees in occupation $k$ working in zone $j$ ($D_{jk}$); and one wants to know the number of employees (in detail types $k = 1, \ldots, K$) that live in $i$, work in $j$, and are of type $k$ ($X_{ijk}$), in other words, journey-to-work flow for type $k$ ($X_{ijk}$). The preferred solution is to make special tabulations of the $X_{ijk}$ from the $X_{ij}$ data in the county-to-county worker flow matrices or CTPP part 3, but these are simply not available due to the different universe from which each CTPP part has been constructed. In the absence of detailed data, one needs to model the $X_{ijk}$ flows, given $S_{ik}$, $D_{jk}$ and with some aggregate control of total $X_{ij}$ that provides the combined flows of all worker types ($X_{ij} = \Sigma_k X_{ijk}$). This is precisely the way the data in the previous section are set up (see chapter 3).
part 1 provides $S_{ik}$, part 2 provides $D_{jk}$ and county-to-county worker flow files contain total worker flow ($X_{ij}$). Further, the issue of consistency between the three parts of data has been addressed by adding one external zone (see figure 1).

The information-minimizing method is perfectly suited to devising the missing details in a way that is maximally consistent with the known data and at the same time non-committal with respect to the missing data: it does so by using a prior to weight the $Q_{ijk}$ which can be used for example to make the weight of the interactions reflect distance decay effects (Fotheringham and O’Kelly, 1989; see also Sweeney, 1999).

**Information minimizing model (IM)**

\[
\text{Minimize} \quad T^{\text{PRED}} = \sum_{i}^{n+1} \sum_{j}^{n+1} \sum_{k}^{K} X_{ijk} \ln\left(\frac{X_{ijk}}{Q_{ijk}}\right) \tag{4.7}
\]

subject to

\[
\sum_{j}^{n+1} X_{ijk} = S_{ik} \quad \forall i, k \tag{4.8}
\]

\[
\sum_{i}^{n+1} X_{ijk} = D_{jk} \quad \forall j, k \tag{4.9}
\]

\[
\sum_{k}^{K} X_{ijk} = X_{ij} \quad \forall i, j \tag{4.10}
\]

Constraint (4.8) requires that the sum of the trips produced from zone $i$ of type $k$ matches the observed numbers of such workers, namely $S_{ik}$. Similarly, constraint (4.9) requires
that the sum of the trips ending in zone \( j \) of type \( k \) matches the observed number of such workers, namely \( D_{jk} \). Finally, constraint (4.10) asks that the sum of the detailed estimated tables \( X_{ijk} \) (combination of \( i, j, k \)) add up to the observed values of interaction \( X_{ij} \), the total worker flow taken from the county-to-county worker flow. For now, we are using the aggregate interaction and the \( Q_{ijk} \) priors to guide the in-fill of the missing detailed interactions at the level of the worker type.

In the following, \( Q \) is a prior weight. For example, \( Q \) could be a negative exponential distance decay effect. From equations (4.7) through (4.10),

\[
X_{ijk} = Q_{ijk} \exp(-\theta_k - \beta_{jk} - \gamma_{ij})
\]  

(4.11)

where \( \theta, \beta, \) and \( \gamma \) are the lagrangean multipliers associated with constraints (4.8) – (4.10).

Then, combining and substituting all the derived multipliers produces the following.

\[
X_{ijk} = Q_{ijk} [A_{ik} S_{ik}] [B_{jk} D_{jk}] [C_{ij} X_{ij}]
\]  

(4.12)

Where

\[
A_{ik} = \frac{1}{\sum_{j}^{n+1}} Q_{ijk} [B_{jk} D_{jk}] [C_{ij} X_{ij}]
\]

\[
B_{jk} = \frac{1}{\sum_{i}^{n+1}} Q_{ijk} [A_{ik} S_{ik}] [C_{ij} X_{ij}]
\]

\[
C_{ij} = \frac{1}{\sum_{k}^{K}} Q_{ijk} [A_{ik} S_{ik}] [B_{jk} D_{jk}]
\]

An iterative algorithm then suggests itself: set \( C \), and iterate \( A \) and \( B \) until (4.8) and (4.9) are satisfied, and then reset \( C \) and redo. This method has been programmed in Visual
Basic and the resulting disaggregated $X_{ijk}$ tables are found to satisfy all the data constraints. The results are then fed into the empirical analysis, where the estimated disaggregate flows are compared to optimal results from an LP benchmark program.
4.3 Cost minimization of journey-to-work flow by type of occupation

This section presents a disaggregated linear program to optimize journey-to-work flow by occupation. Utilizing the well-known transportation problem, theoretical minimum commutes by type of occupation are calculated from the optimized individual journey-to-work flow.

**Disaggregated Transportation Problem (DTP)**

\[
\text{Minimize} \quad T^{\text{MIN}} = \frac{1}{W} \sum_{i=1}^{n+1} \sum_{j=1}^{n+1} \sum_{k=1}^{K} X_{ik} Y_{ij}
\]

subject to

\[
\sum_{i=1}^{n+1} X_{ik} = D_{jk} \quad \forall j, k
\]

\[
\sum_{j=1}^{n+1} X_{ik} = S_{ik} \quad \forall i, k
\]

\[
\sum_{i=1}^{n+1} \sum_{k=1}^{K} X_{ik} = D_j \quad \forall j = 1, \ldots, n + 1
\]

\[
\sum_{j=1}^{n+1} \sum_{k=1}^{K} X_{ij} = S_i \quad \forall i = 1, \ldots, n + 1
\]

\[
\sum_{i=1}^{n} \sum_{k=1}^{K} X_{ik} = d_j \quad \forall j = 1, \ldots, n
\]

\[
\sum_{j=1}^{n} \sum_{k=1}^{K} X_{ij} = s_i \quad \forall i = 1, \ldots, n
\]

\[
\sum_{i=1}^{n+1} \sum_{j=1}^{n+1} X_{ij} = X_k \quad \forall k
\]

\[
X_{ik} \geq 0 \quad \forall i, j, k
\]
where total costs are averaged by total workers, $W$, in the original journey-to-work matrix \((n \times n)\). Note that the dimension of the extended O-D matrix is expressed as \((n+1) \times (n+1)\). Constraint (4.14) ensures that the sum of trips ending in \(j\) of type \(k\) matches the observed numbers for each group. And constraint (4.15) ensures that the sum of trips originating from \(i\) of type \(k\) also matches the observed numbers for each group. Constraint (4.16) ensures that sum of all workers ending in \(j\) should be equal to total number of workers in the extended OD matrix \(((n+1) \times (n+1))\). Similarly, constraint (4.17) ensures that sum of all workers originating from \(i\) should be equal to total number of workers in the extended OD matrix \(((n+1) \times (n+1))\). Constraints (4.18) and (4.19) are the same as (16) and (17), but they are applied for the original OD matrix \((n \times n)\). Constraint (4.20) requires total number of workers for each group should be maintained. The model produces 6 individual OD matrices obeying all constraints. The LP models have been coded in MATLAB and solved in a commercial optimization package.

4.4 Excess commuting by type of occupation: 1990 - 2000

Application results are presented in Table 4.1. Predicted average commute lengths \((T^{PRED})\) are derived from the results of the information minimization (IM) model (equation (4.7)). By computing the following equation (4.23) for each disaggregated OD matrix obtained from the IM model produces \(T^{PRED}\) for each occupation.

\[
\frac{1}{W_k} \sum_{i}^{n} \sum_{j}^{n} X_{ijk} Y_{ij}
\]  

(4.22)

where $W_k$ is the total for the $k^{th}$ group.
Minimum commute lengths ($T^{MIN}$) are derived from the solution to the disaggregated transportation problem (equation (4.13)). Computation is exactly the same as equation (4.22).

Excess commuting is calculated as follows:

$$\text{Excess (\%)} = 100 \times \left[ \frac{X^{PRED} - X^{MIN}}{X^{PRED}} \right]$$  (4.23)

Results of predicted trip length distributions ($T^{PRED}$) for each occupation vary from 14.84 to 15.90 miles in 1990 and 15.35 to 16.43 miles in 2000. Minimum average commutes ($T^{MIN}$) vary from 12.33 to 14.79 miles in 1990 and from 12.58 to 14.99 miles in 2000, respectively. A general trend is found in that all occupations have gained commuting miles with no exceptions for the ten-year period between 1990 and 2000.

Workers in farming, forestry, and fishing occupations appear to make the shortest commute in both years. In terms of the longest commute, military workers show the highest commuting miles in 1990 (15.90 miles) while workers in transportation and production become the highest commuting group in 2000 (16.43 miles). As identified in Giuliano and Small (1993) and Horner (2002), each occupational group shows varying levels of trip length distributions. While the aggregate minimum average commute is 12.94 miles in 1990 and 13.14 miles in 2000, disaggregate minimum commutes vary from 12.33 to 14.79 miles in 1990 and from 12.58 to 14.99 miles in 2000, respectively. Workers in farming, forestry, and fishing show the lowest minimum commutes in 1990.
(12.33 miles). However, in 2000, service workers have the lowest minimum commutes (12.58 miles) opposed to the highest for workers in military occupations. As consistent with Giuliano and Small (1993) and Horner (2002), service workers show relatively low minimum commutes for both years.

From the commuting efficiency aspect, excess commuting can explain whether certain types of workers make journey-to-work trips more or less efficiently than others. At the aggregate, excess commuting has increased from 15.3% in 1990 to 16.9% in 2000. At the disaggregate, excess commuting varies from 7.0 to 17.2% in 1990 and from 6.1 to 18.9% in 2000 with the mixture of trends. In both years, service occupations have the highest levels of excess commuting (17.2% in 1990 and 18.9% in 2000) while military workers are the lowest (7.0% in 1990 and 6.1% in 2000). It is interesting that workers in managerial and professional occupations sales occupations are getting relatively higher percent of excess commuting in 2000 compared to 1990 with other groups.

These results imply non-uniform levels of excess commuting and jobs/workers ratios. The proposed models are expected to have a wide range of uses in measurement and assessment of empirical patterns of commuting. The scope of the disaggregation can be extended to other targets such as different types of industry, household structure, income level, ethnic background, education level, transportation mode, and gender. Further dimensions of disaggregation can address spatial interactions of different socio-economic groups in urban areas, and more generally, contribute to exploring urban sprawl according to job characteristics and industries.
<table>
<thead>
<tr>
<th>Occupations</th>
<th>( T^{\text{MIN}} ) (miles)</th>
<th>( T^{\text{PRED}} ) (miles)</th>
<th>Excess commuting (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All occupations</td>
<td>12.94</td>
<td>13.14</td>
<td>15.28</td>
</tr>
<tr>
<td>Managerial and professional occupations</td>
<td>12.79</td>
<td>12.98</td>
<td>15.04</td>
</tr>
<tr>
<td>Sales occupations</td>
<td>12.87</td>
<td>13.05</td>
<td>15.11</td>
</tr>
<tr>
<td>Service occupations</td>
<td>12.46</td>
<td>12.58</td>
<td>15.05</td>
</tr>
<tr>
<td>Farming, forestry, and fishing occupations</td>
<td>12.33</td>
<td>13.00</td>
<td>14.84</td>
</tr>
<tr>
<td>Transportation and production occupations</td>
<td>13.34</td>
<td>13.65</td>
<td>15.78</td>
</tr>
<tr>
<td>Military occupations</td>
<td>14.79</td>
<td>14.99</td>
<td>15.90</td>
</tr>
</tbody>
</table>

Table 4.1 Analysis results for the tri-state area
4.5 Job-housing balance in the tri-state area

The solutions obtained from the information minimization (IM) model are valuable to address jobs-housing balance in greater detail by occupational group, which has not been substantially studied in the past. The jobs/workers ratio, one of the common measures of jobs-housing balance (Bookout, 1990), is presented in Figures 4.2 and 4.3 for service workers and transportation and production workers.

The ratio is calculated as follows:

\[ V_{lk} = \frac{\sum_{i} X_{ilk}}{\sum_{j} X_{ijk}} \]  

(4.24)

where each worker type, \( k \), is inserted.

The jobs/workers ratio, \( V_{lk} \), is computed for zone \( l \) in occupation group \( k \). If \( V_{lk} \) is greater than 1, the zone \( l \) is “rich” for job \( k \). If \( V_{lk} \) is less than 1, then the zone \( l \) is “poor” for job \( k \). Disaggregating jobs/workers ratio by worker type can accurately answer questions such as, “which areas have surplus service jobs?” and, “which areas need more service jobs?” These two questions should be answered in order to detect any disparity between supply of and demand for workers. Moreover, it is expected that some areas may have surplus for a certain job type but a lack of another job type. Investigating varying levels of jobs/workers ratio for occupational type will help identify the urban structure based upon different distributions of workers and jobs. By doing this, we can further address diverse regional contexts. As seen in excess commuting, jobs/workers ratios also show
non-uniform patterns among occupational types. The aggregate jobs/workers ratio should be 1 because we used balanced or closed journey-to-work data. However, once aggregate data is broken down to each county by occupation type, the ratios vary significantly.
Figure 4.2 Job-rich counties for service employment
Figure 4.3 Job-rich counties for transportation and production employment
A. Service

B. Transportation and production

Figure 4.4 County-to-county worker flows (2000)
4.6 Discussion

Several statements can be made regarding the analytical results. First, results verify the varying levels of actual trip length and excess commuting. Findings are that that workers in transportation and production occupations and military occupations make longer journey-to-work trips while workers in farming, forestry, and fishing occupations and service occupations make shorter trips in both years. In terms of excess commuting, service workers in both years show the highest excess commuting. On the other hand, the lowest excess commuting is detected for military workers. These results may be explained in terms of the degree of dispersion of the destinations; well-defined destination/attractors generate efficient travel patterns, while more dispersed activities invariably produce varied trip making responses and allow for greater ranges in commuting distances. Second, the proposed models control for the total aggregate flow by which consistency between aggregate and disaggregate journey-to-work data is maintained. Third, it should be emphasized that not all occupational groups show consistent results with previous works reported in Horner (2002) and Giuliano and Small (1993). This implies that we should take the different geographical contexts into account because varying levels of actual trip length may be seen as a product of the spatial structure. It is understood, for instance, that service workers in different regions may not have identical trip patterns because of different distributions of jobs and housing.

Some further thoughts are now addressed. Since we assumed fixed locations of residence and employment, current spatial structure is embedded in the journey-to-work data. One of the key issues is that aggregate measures for excess commuting or jobs-housing
balance cannot accurately reflect spatial interactions of different socio-economic groups. In terms of spatial structure, locations of residence and employment for two representative groups (service occupations and transportation and production occupations) where contrasting patterns are detected.
CHAPTER 5 A DISAGGREGATE ANALYSIS OF ACCESSIBILITY

Analysis in the previous chapter has shown the importance of disaggregating journey-to-work data by verifying non-uniform levels of excess commuting and jobs-housing balance by occupation. Since disaggregated trip distribution models have been developed, further analysis through the application of the IM model may offer another dimension to explore occupational variations in accessibility patterns. By doing so, one can detect locational accessibility to a certain type of jobs and a certain type of workers, which is useful to measure the growth potential of employment or residential development.

This chapter employs a comparative view on locational accessibility differentiated by type of workers. Locational accessibility is examined for 6 occupational groups and visualized in 1990 and 2000 at the county level. Utilizing the information minimization (IM) model in the chapter 4, balancing factors of each occupation are employed as surrogates for accessibility with respect to residential and employment locations, respectively. Such a disaggregated analysis of accessibility has not been studied due to the lack of detailed data and methodological frameworks, which limits obtaining individual journey-to-work flow estimate by occupation. This chapter models and
visualizes accessibility patterns in 1990 and 2000 using geographic information systems (GIS).

5.1 Spatial Interaction Model and Accessibility

A basic notion of the spatial interaction (SI) model is that the interactions between two places are positively related with their size (e.g. population, jobs) and negatively related with their spatial deterrence (e.g. distance, time). Wilson (1967) provides a rationale of the spatial interaction model by developing the entropy-maximizing framework. The core idea is to apply the concept of entropy to human behavior. Wilson (1967) derives a family of spatial interaction models within this entropy-maximizing framework and establishes a concrete foundation for journey-to-work flow estimation. This framework predicts the most probable distribution of microstates based on given information of macrostates (Fotheringham and O’Kelly, 1989; Miller and Shaw, 2001). In the trip distribution table, microstates are the journey-to-work flows and macrostates are row and column sums. Wilson’s derivation of spatial interaction models has been applied to a wide range of research on migration, market area analysis, and commuting behavior (Fotheringham and O’Kelly 1989).

This chapter primarily focuses on the doubly constrained spatial interaction model where the sum of outbound flows from trip origins and the sum of inbound flows to trip destinations are exogenous. The doubly constrained SI model is especially appropriate for a commuting study since the trip production and trip attraction are both known. These
two exogenous information are set up as origin and destination constraints so that the estimation of the journey-to-work trips preserves the given information. The general doubly constrained SI model is constructed as follows:

\[ X_{ij} = A_i S_i B_j D_j f( c_{ij} ) \]  \hspace{1cm} (5.1)

\[ A_i = \left( \sum_j B_j D_j f( c_{ij} ) \right)^{-1} \]  \hspace{1cm} (5.2)

\[ B_j = \left( \sum_i A_i S_i f( c_{ij} ) \right)^{-1} \]  \hspace{1cm} (5.3)

subject to

\[ \sum_j X_{ij} = S_i \] \hspace{1cm} (generally ensured by equation 5.2) \hspace{1cm} (5.4)

\[ \sum_i X_{ij} = D_j \] \hspace{1cm} (generally ensured by equation 5.3) \hspace{1cm} (5.5)

where

\( i \) = index of origins

\( j \) = index of destinations

\( X_{ij} \) = interaction between \( i \) and \( j \)

\( S_i \) = number of workers in origin \( i \)

\( D_j \) = number of jobs in destination \( j \)

\( A_i \) = row balancing factors

\( B_j \) = column balancing factors

\( f( ) \) = function of distance deterrence

\( c_{ij} \) = travel costs between \( i \) and \( j \)

Equation (5.1) is the general form of the doubly constrained spatial interaction model and equations (5.2) and (5.3) are the row and column balancing factors, respectively. These factors are origin (\( A_i \)) and destination (\( B_j \)) specific, so that interaction flows are predicted.
as well as possible to the observed flows. The model is constrained by the origin
cstraint (equation (5.4)) to ensure that the row sum of each zone is equal to the given
information. Similarly, the column sum of each zone is constrained by equation (5.5) to
match the given information. The model contains the spatial deterrence function, $f()$,
which reflects the relationships between travel costs (e.g. distance or time) and the
volume of interaction (e.g. number of work trips). One representative deterrence function
is the negative exponential (Fotheringham and O’Kelly 1989, Horner 2004).

The standard doubly constrained SI model produces “normalizing” or “balancing” factors
for origins (equation (5.2)) and destinations (equation (5.3)). These balancing factors
have drawn attention from researchers as accessibility measures (Kirby 1970, Cesario
factors as accessibility measures as follows.

“…, the terms $(1/A_i)$ and $(1/B_j)$ are in fact measures of accessibility (and not merely
“related” to accessibility as Wilson stated). Specifically, the terms $(1/A_i)$ measures the
accessibility of destinations with respect to origin $i$ and $(1/B_j)$ measures the accessibility
of origins with respect to destination $j$.”

Origin or residential accessibility scores are obtained from the inverse of row balancing
factors. Following up Cesario’s argument, Harris (2001) points out that balancing factors
are similar to the inverse of Hansen-type accessibility measures. For example, the
difference between origin balancing factors (equation 5.2) and the Hansen-type
accessibility is the existence of a demand side weight, $B_j$. Horner (2004) explains this as
an advantage in that origin balancing factors can take both supply and demand accessibility into account simultaneously unlike Hansen-type accessibility measures. Horner argues that a regional factor may not necessarily only limit origins, rather it can be a combination of supply and demand as origin and destination at the same time. This explanation provides a strong justification to use balancing factors as accessibility measures. The inverse of origin balancing factors, \((A_i)^{-1}\), is the total accessibility from an origin \(i\) (e.g. home locations) to reach opportunities (e.g. job locations) at all \(j\) by the distance decay function. Similarly, destination accessibility scores are obtained from the inverse of \(B_j\). The inverse of column balancing factors, \((B_j)^{-1}\), is indicative of the ability to reach opportunities at all origins \(i\) from a destination \(j\) (e.g. job locations). In other words, \((A_i)^{-1}\) is the employment accessibility with respect to origin \(i\), and \((B_j)^{-1}\) is the residential accessibility with respect to destination \(j\). In the commuting context, \((A_i)^{-1}\), or employment accessibility measures the ability to produce trips from \(i\) to employment locations. Similarly, \((B_j)^{-1}\) or residential accessibility measures the ability to attract trips to \(j\) from residential locations.

5.2 Disaggregated accessibility by occupational type

Discussion on balancing factors in the general SI model has been made in the previous section. The information minimization (IM) model in the chapter 4 produces balancing factors to measure residential and employment accessibility scores for heterogeneous occupations. Recall that the IM model estimates the most likely distribution of journey-to-work flow for each occupation that adds up to the total number of workers. Row and
column sums for each occupation are given while individual journey-to-work flows for each occupation are unknown. In such a disaggregated analysis, an additional index of occupation, $k$, has been incorporated. The balancing factors can be obtained from the IM model as follows:

\[
\text{Minimize } \sum_{i}^{n+1} \sum_{j}^{n+1} \sum_{k}^{K} X_{ijk} \ln(X_{ijk} / Q_{ijk}) \tag{5.6}
\]

\[
A_{ik} = \left( \sum_{j}^{n+1} Q_{ijk} [B_{jk} D_{jk}] [C_{ij} X_{ij}] \right)^{-1} \tag{5.7}
\]

\[
B_{jk} = \left( \sum_{i}^{n+1} Q_{ijk} [A_{ik} S_{ik}] [C_{ij} X_{ij}] \right)^{-1} \tag{5.8}
\]

\[
C_{ij} = \left( \sum_{k}^{K} Q_{ijk} [A_{ik} S_{ik}] [B_{jk} D_{jk}] \right)^{-1} \tag{5.9}
\]

subject to

\[
\sum_{j}^{n+1} X_{ijk} = S_{ik} \quad \forall i, k \tag{5.10}
\]

\[
\sum_{i}^{n+1} X_{ijk} = D_{jk} \quad \forall j, k \tag{5.11}
\]

\[
\sum_{k}^{K} X_{ijk} = X_{ij} \quad \forall i, j \tag{5.12}
\]

where

$k$ = index of occupations

$A_{ik}$ = origin balancing factors associated with $k$

$B_{jk}$ = destination balancing factors associated with $k$

$C_{ij}$ = balancing factors associated with $k$
The information minimization (IM) model (equation 5.6) predicts individual journey-to-work flow for each occupation, $k$. This information-minimizing framework is suited to estimate the missing details in a way that is maximally consistent with the known data and at the same time non-committal with respect to the missing data. By using a prior to weight the $Q_{ijk}$, the interactions are weighted to reflect distance decay effects (Fotheringham and O’Kelly, 1989; see also Sweeney, 1999). Equations (5.7) and (5.8) are row and column balancing factors, both specific for a group $k$. Equation (5.9) are balancing factors associated with occupational groups. Equations (5.10) and (5.11) are origin and destination constraints that must be preserved for group $k$ in each zone. Equation (5.12) is unique to this IM model since it ensures that the interactions between two places ($i$ and $j$) for group $k$, $X_{ijk}$, should add up to the total interactions between $i$ and $j$, $X_{ij}$. Note that $X_{ij}$ is given and $X_{ijk}$ is unknown to be estimated.

Applying Cesario’s argument, the IM model also produces balancing factors that can be used as detailed accessibility measures. While Wilson’s approach produces two balancing factors for each zone, one as origin and the other as destination, the IM model generates $2k$ balancing factors for each zone since an additional index, $k$, has been incorporated. Note that $k$ represents the number of occupational groups. This is an improvement in that one can now explore detailed accessibility differentiated by occupational type. This also makes better sense because the notion of accessibility should reflect people’s behavior in a more detailed fashion. As argued before, nonsensical errors may occur when one ignores worker types and therefore accessibility, too, should be differentiated by type of workers.
5.3 Empirical analysis

This section explores spatial patterns of accessibility for the tri-state counties through the concept of normalizing or balancing factors obtained from the information minimization (IM) model. To provide a comparative view, both 1990 and 2000 data have been modeled and analyzed. Accessibility is disaggregated according to 6 occupational groups. Due to a number of accessibility scores by origin, destination, and occupation for 1990 and 2000, two representative occupational groups are selected for analysis and visualization. Service occupations and transportation and production occupations are representative groups in this section. For convenience, the latter group will be labeled as transportation occupations. Table 5.1 summarizes analysis results in terms of county rankings with high accessibility scores and accessibility change between 1990 and 2000. Figures 5.1 through 5.8 visualize the results to provide various views on accessibility patterns and trip emission and attraction to detect spatial variations differentiated by occupational type.

5.3.1 Visualizations of accessibility and change

Employment and residential accessibility show their highest scores in major urban counties (Table 5.1, Figures 5.1 and 5.2). This implies that the core counties of major metropolitan statistical areas (MSAs) are dominant employment centers and producers of worker supply at the same time. This makes sense at the county level due to high percentage of intra-county commuting flow. The core urban counties such as Cuyahoga county in Cleveland MSA, Franklin county in Columbus MSA, Hamilton county in Cincinnati MSA, and Marion county in Indianapolis MSA are all ranked within the top
five most accessible counties to service and transportation jobs both in 1990 and 2000 (Table 5.1). Residential accessibility shows similar rankings with small changes. Overall, spatial patterns are not strikingly different, though employment accessibility of service occupations is slightly more spread than its residential accessibility in 2000 (Figure 5.1). This trend becomes clearer for transportation occupations whose employment centers are major MSA areas in the tri-state region (Figure 5.2). Major urban counties tend to possess higher propensity to attract work trips as destinations than to produce work trips as origins.

In addition to exploring accessibility itself, it may be interesting to explore temporal changes of accessibility between 1990 and 2000 to identify whether there has been a sign of suburbanization trends. The last two columns of the Table 5.1 rank top five counties according to the highest increase of employment and residential accessibility for two occupational groups. Spatial patterns of accessibility change are illustrated in Figures 5.3 and 5.4.

Service and transportation occupations reveal different patterns of accessibility change both in employment and residential sides. Strikingly, none of the core urban counties are ranked in any category of accessibility change (see last two columns in Table 5.1). In terms of employment accessibility change for service jobs, Ohio county in Indiana shows the highest with a 168% increase followed by Dearborn, IN (93%), Wolfe, KY (89.9%), Switzerland, IN (75.2%), and Delaware, OH (67.7%) counties. Ohio and Dearborn counties in Indiana are part of Cincinnati MSA and Switzerland county is bordering
Cincinnati MSA. Delaware in Ohio is a Columbus MSA county. Except Wolfe county in Kentucky, the other top four counties are also suburban-type areas in major MSAs. Interestingly, the top five counties are all Kentucky counties for the accessibility change of transportation employment. Spencer county in Kentucky shows the highest of a 190% increase in transportation employment accessibility. The other four counties show much less increase ranging from 92.8% (Scott, KY) down to 83.2% (Gallatin, KY). These top five Kentucky counties are not central cores of their MSA, rather they are more suburban-type areas. Grant, Boone, and Gallatin counties (in Kentucky) are in Cincinnati MSA, Scott county in Lexington MSA, and Spencer county is expected to be included in Louisville MSA in the next census. Unlike major urban counties, these suburban counties may have less saturation level in job markets so that their accessibility has increased dramatically. Taking advantage of easy access to major urban centers, these counties may have grown rapidly as targets of employment suburbanization. Given that Spencer county will be part of Louisville MSA in the next census, it is not surprising to see this significant increase as a sign of the rapidly growing level of interactions with Louisville MSA.

In general, employment accessibility change has occurred mostly in suburban counties both for service and transportation jobs. Even though their spatial patterns may not be the same, it is possible to argue that employment accessibility in suburban counties has increased exceeding that of major urban counties. Cuyahoga county, for instance, has experienced loss of its employment accessibility both for service and transportation jobs, which implies the suburbanization of employment.
Unlike employment accessibility change, residential accessibility has changed differently. The top five counties in residential accessibility change show a mixture of suburban and rural characteristics. Ohio county of Indiana in particular is ranked at the top in residential accessibility change in both categories with a 172% increase for service and 117.9% for transportation workers. Scott in Kentucky and Hamilton in Indiana are also ranked as top five counties. A noticeable result is that rural counties such as Clinton and Perry counties in Kentucky are ranked within the top five in service and transportation jobs, respectively. This can be explained in a relative sense since Perry county has experienced 50.1% loss of employment accessibility for transportation related jobs and Clinton county has lost more than 6% of employment accessibility for service jobs. Due to their remote geographic location and the difficulty attracting workers, residential accessibility may have increased much higher than other counties.

In general, residential accessibility has increased in suburban counties as well as rural counties for both occupations. However, their spatial distributions are quite different (see Figures 5.3 and 5.4). One noticeable difference is that south-central Kentucky counties have gained higher increase of residential accessibility for service workers opposing significant loss for transportation workers. This finding supports the needs of temporal trend analysis since it allows to view how the spatial structure has been altered and furthermore to predict future possibility of development at a larger scale.
An interesting finding is that the highest accessibility change is detected in suburban counties of major cities rather than the core urban counties. Residential accessibility for service workers shows the highest increases around major metropolitan areas while employment accessibility show somewhat lesser degree of gains. To the contrary, workers in transportation jobs experience more striking accessibility changes. Southeastern Kentucky has lost its employment accessibility while residential accessibility has increased. It is not surprising that southeastern Kentucky has poor access to major transportation routes and hence it is not likely to attract workers in transportation and production. Counties that are not located close to major urban counties tend to have opposing trend in that residential accessibility increases as employment accessibility decreases. This result is consistent with Horner’s (2004) argument since accessibility from the spatial interaction model simultaneously captures supply and demand side accessibility.

By looking at spatial distributions of accessibility by occupation over the ten-year period between 1990 and 2000, several trends have been identified. First, major urban counties have high levels of residential and employment accessibility. Second, changes in accessibility have been identified differentiated by occupation implying suburbanization trends of employment and residences. Third, the highest increase of employment accessibility is detected mostly in suburban counties while residential accessibility has increased both in suburban and non-suburban counties.
<table>
<thead>
<tr>
<th>Service</th>
<th>Employment accessibility</th>
<th>Residential accessibility</th>
<th>Emp. Acc. increase (%)</th>
<th>Res. Acc. increase (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Franklin, OH</td>
<td>Franklin, OH</td>
<td>Cuyahoga, OH</td>
<td>Cuyahoga, OH</td>
</tr>
<tr>
<td>2</td>
<td>Cuyahoga, OH</td>
<td>Cuyahoga, OH</td>
<td>Hamilton, OH</td>
<td>Franklin, OH</td>
</tr>
<tr>
<td>3</td>
<td>Hamilton, OH</td>
<td>Hamilton, OH</td>
<td>Marion, IN</td>
<td>Marion, IN</td>
</tr>
<tr>
<td>4</td>
<td>Marion, IN</td>
<td>Marion, IN</td>
<td>Franklin, OH</td>
<td>Hamilton, OH</td>
</tr>
<tr>
<td>5</td>
<td>Jefferson, KY</td>
<td>Lake, IN</td>
<td>Jefferson, KY</td>
<td>Jefferson, KY</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Transportation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>5</td>
</tr>
</tbody>
</table>

**Table 5.1 County rankings of high accessibility and increase**
A. Employment accessibility (2000)

B. Residential accessibility (2000)

Figure 5.1 Accessibility of workers in service occupations (2000)
A. Employment accessibility (2000)

B. Residential accessibility (2000)

Figure 5.2 Accessibility of workers in transportation occupations (2000)
Figure 5.3 Accessibility changes for service occupations 1990-2000
Figure 5.4 Accessibility changes for transportation occupations 1990-2000
5.3.2 Propensity of trip attraction and emission

Another use of the balancing factors is to measure propensity of trip emission labeled as “emissiveness” with respect to origin \(i\) and trip attraction labeled as “attractiveness” with respect to destination \(j\) (Cesario 1977). Multiplying balancing factors by \(S_i\) and \(D_j\) calculates emissiveness and attractiveness, respectively as follows:

\[
Emissiveness = A_i S_i = \frac{S_i}{\sum_j B_j D_j \exp(-\beta c_{ij})}
\]

\[
Attractiveness = B_j D_j = \frac{D_j}{\sum_i A_i S_i \exp(-\beta c_{ij})}
\]

Extending the same concept to occupational groups produces the following disaggregated measures of emissiveness and attractiveness, respectively:

Relative emissiveness

\[
A_{ik} S_{ik} = \frac{S_{ik}}{\sum_j Q_{ijk} [B_{jk} D_{jk}] [C_{ij} X_{ij}]}
\]

Relative attractiveness

\[
B_{jk} D_{jk} = \frac{D_{jk}}{\sum_i Q_{ijk} [A_{ik} S_{ik}] [C_{ij} X_{ij}]}
\]

The above incorporates weights that are supply and demand of a zone, respectively. Supply is a zone’s total number of resident workers and demand is a zone’s total number of jobs. Emissiveness then measures the inclination of producing work trips “relative” to
other zones and similarly attractiveness measures the propensity of attracting work trips “relative” to other zones (Cesario 1974; Thomas 1977). Here the meaning of “relativeness” should be clarified. According to Thomas (1977), both measures are “behavioral” indices that tend to increase as emissiveness and attractiveness increase. Zones with high values of emissiveness and attractiveness are actually inaccessible zones yet they produce or attract a large volume of work trips (Horner 2004). In his sample study of Atlanta area, Horner finds that highly emissive zones tend to locate in the edges of the area. This is an extremely useful point in that one can detect decentralization trends of residential areas spreading out of the centers. In the case of attractiveness, highly attractive zones are clustered in the city center while several suburban employment centers are identified, too. However, accessibility itself contrasts with emissiveness or attractiveness because emissiveness, for instance, actually contains an “inaccessibility” component. Mathematically, equations (5.13) and (5.14) incorporate $A_i$ and $B_j$ and give lower scores to high accessibility zones. This is consistent with Horner’s findings since emissiveness and attractiveness actually address “inaccessibility” weighted by supply and demand of a zone so that outliers absorbing or emanating large work trips are visible. A simple modification of emissiveness and attractiveness then adds another dimension to measure “true” emissive and “true” attractive zones that should have consistent spatial patterns with residential and employment accessibility patterns shown in Figures (5.1) and (5.2). Hence, accessibility derived from balancing factors should be used as a form of “the inverse of balancing factors”. However, in the calculations of emissiveness and attractiveness, balancing factors are directly incorporated resulting in the form of (5.13)
and (5.14). Now one can simply manipulate equations (5.13) and (5.14) in order to detect zones that are actually true “residential” and “employment” centers as follows.

Absolute emissiveness

\[
(A_{ik})^{-1} S_{ik} = S_{ik} \left( \sum_j Q_{ijk} [B_{jk} D_{jk} [(C_{ij} X_{ij})] \right)
\]

(5.17)

Absolute attractiveness

\[
(B_{jk})^{-1} D_{jk} = D_{jk} \left( \sum_i Q_{ijk} [A_{ik} S_{ik} ] [C_{ij} X_{ij}] \right)
\]

(5.18)

Once the inverse of balancing factors is weighted by supply and demand of workers in a zone, one can identify true residential and employment centers. It is expected that the comparison of equations (5.13) and (5.14) with (5.15) and (5.16) would show non-uniform or contrasting spatial distributions. For instance, (5.13) and (5.14) are expected to reveal suburban areas that tend to produce or attract workers despite of their inaccessible locations and (5.15) and (5.16) will identify core centers of residence and employment. Note that an index, \(k\), is added to all calculations so that occupational characteristics are explicitly addressed. Figures (5.5) and (5.6) visualize trip attraction by occupation and Figures (5.7) and (5.8) visualize trip emission by occupation in 1990 and 2000.

Not surprisingly, both absolute emissiveness and attractiveness for service and transportation workers (see Figures (5.6) and (5.8)) show similar patterns with accessibility patterns in Figures (5.1) and (5.2). However, in a relative sense, spatial patterns are strikingly contrasting with absolute measures and between occupational
groups. Counties with high relative attractiveness to service jobs are detected in Hamilton county Indiana, which is part of Cincinnati MSA and eastern Kentucky region. For the transportation employment, high scores of relative attractiveness more scattered along the counties that have access to transportation routes (see Figure 5.5). These results are consistent with Figures (5.3) and (5.4) where counties with high accessibility change are visualized (See also Table 5.1). Most of high ranked counties in employment accessibility increase show high values of relative attractiveness. Relative emissiveness, however, are more widely distributed and shows reversed patterns from the relative attractiveness (see Figure 5.7). It becomes now that at the county level relative measures are suitable to detect areas that have possibility to be future targets of employment suburbanization. Major core urban counties have not been distinguished in relative attractiveness yet they are still dominant employment centers with high absolute attractiveness and employment accessibility.
A. Relative propensity of trip attraction for service occupations (2000)

B. Relative propensity of trip attraction for transportation occupations (2000)

Figure 5.5 Relative propensity of trip attraction (2000)
A. Absolute propensity of trip attraction for service occupations (2000)

B. Absolute propensity of trip attraction for transportation occupations (2000)

Figure 5.6 Absolute propensity of trip attraction (2000)
A. Relative propensity of trip emission for service occupations (2000)

B. Relative propensity of trip emission for transportation occupations (2000)

Figure 5.7 Relative propensity of trip emission (2000)
A. Absolute propensity of trip emission for service occupations (2000)

B. Absolute propensity of trip emission for transportation occupations (2000)

Figure 5.8 Absolute propensity of trip emission (2000)
5.4 Summary and Discussion

First, SI model based accessibility itself is useful to explore employment centers and dominant residential areas. As an extended and disaggregated measure, occupational characteristics are explicitly addressed and temporal change has been presented. Second, the major urban counties are ranked high in both employment and residential centers while suburban counties in or close to major MSAs have gained highest accessibility increases between 1990 and 2000. This enables visualization of potential future sprawl by capturing rapidly growing interactions between MSA and non-MSA counties. Spencer county in Kentucky, for example, is not part of any major MSAs but has experienced a dramatic accessibility increase (190.0%) in employment accessibility for transportation jobs. Third, uniqueness in this dissertation is to capture inter-state journey-to-work flow since many MSAs often consists of counties across two or more states. Cincinnati is a perfect example consisting of counties from three states. This chapter has pointed that suburban counties of Cincinnati MSA has increased their employment accessibility owing to easy access to major urban county (Hamilton county Ohio). Fourth, occupational variations are identified in most of analysis in this chapter. As argued in previous chapters, disaggregation according to worker type or other socio-economic characteristics of workers or jobs should be explicitly addressed. Ignoring heterogeneity of workers may lead to disguising results since all workers are assumed to be the same no matter what their jobs are. Using two representative occupational groups (service and transportation), one can now confirm variations in spatial structure of accessibility, attractiveness, and emissiveness. An interesting finding is that none of highly ranked
counties in employment accessibility change in service jobs is dropped out of the top five
counties in the case of transportation jobs. This implies non-uniform spatial structure
according to job types and may reflect regional contexts.
This chapter assesses the impacts of multiple policy scenarios on commuting. Policy scenarios explicitly address inbound, outbound, and intrazonal trips, which is critical for understanding the dynamics of excess commuting and jobs-housing balance. Only a few studies have addressed policy implications through a disaggregated approach to excess commuting and jobs-housing balance. To bridge the gap in the literature, this chapter predicts possible commuting patterns that may be varied through residential and employment relocation policies and, furthermore, by different worker type. Based on the disaggregated linear program (LP) developed in chapter 4, this chapter further extends the model to assess occupational variations under multiple policy scenarios.

The objectives are: (1) to estimate minimum commuting miles when all worker’s residence and employment locations are relocated, (2) to examine impacts of worker shift between outbound and inbound trips on commuting patterns, and (3) to assess hypothetical policy scenarios that are more beneficial to each occupational group. All objectives comprehensively deal with disaggregation according to occupational groups, consistent with previous chapters.
6.1 Jobs-housing balance and dynamic aspect of commuting

Excess commuting and jobs-housing balance originate from the mismatch of residential and job locations. For zones with surplus jobs, this mismatch causes inbound commuting that attracts workers from external zones. When there is a lack of jobs for resident workers, then outbound commuting occurs and resident workers tend to make trips to external zones for their work. In the context of jobs-housing balance, a large volume of outbound commuting implies a job-poor situation while a large volume of inbound commuting is indicative of job-rich situation that is common to employment centers. An underlying assumption here is that jobs-housing balance can be achieved once workers live and work in the same zone. In this situation, a higher percent of intrazonal commuting is maintained, hence, commuting lengths are reduced and self-containment level for a zone increases. Jobs-housing balance is related with higher intrazonal commuting rates, which reduces outbound commuting and shortens average commute lengths simultaneously (Cervero 1996a). As jobs-housing balance pertains to the locational disparity of workers and jobs, it should be noted that intrazonal, inbound, and outbound commuting depend on the size of a zone. When the size of a zone increases, the percent of intrazonal commuting is likely to increase because a larger zone accommodates more jobs and workers. Hence, inbound and outbound commuting decrease due to the longer trip length out of workers’ residential zones. The size of a zone is also related to commuting length in that the average trip length tends to increase as zones are aggregated into much larger units (Horner and Murray 2002).

6.2 Modeling effects of jobs-housing balance policy on commuting

Jobs-housing balance is inherently related to the concept of excess commuting since both deal with locational mismatch of jobs and housing (Horner and Murray 2003). As discussed in previous chapters, excess commuting has widely adopted a linear programming approach to measure the difference between the observed average commute and the theoretical minimum average commute (Giuliano and Small 1993, Scott et al. 1997, Horner 2002, 2004, Horner and Murray 2002). Basic assumptions are: (1) no differentiation in worker types, and (2) residential and job locations are fixed and given. Since the second assumption may provide policy implications, several studies have examined the effects of land use policies on the configuration of jobs and housing (Merriman et al. 1995, Scott and Getis 1998, Horner and Murray 2003). Merriman et al. (1995) examine the impacts of Tokyo’s regional plan on excess commuting. Their modeling approach is to predict levels of excess commuting according to alternative land use policy scenarios. In finding an optimal solution, locations of jobs and housing are
fixed, which makes it impossible to predict reconfiguration of job and housing locations. Scott and Getis (1998) and Horner and Murray (2003) have improved the classical transportation problem by reallocating jobs and housing locations. Scott and Getis (1998) develop a heuristic approach that improves jobs-housing balance by reallocating jobs and housing. When unbalanced zones reach a balanced stage, commuting distance decreases. However, their solution is not guaranteed to be optimal since the procedure is a heuristic. Horner and Murray (2003) present an extended transportation problem to assess jobs-housing balance and commuting relations in Atlanta. Their approach examines various land use policies by allowing workers and jobs to relocate. The results show that relocating workers is more beneficial than relocating jobs and that the greatest reductions in the average minimum commute is achieved by relocating workers only. One of limitations of Horner and Murray is the homogeneity assumption of workers. All workers in the region are treated as being in the same group without differentiating their worker types.

An issue here is “jobs-housing balance for which type of workers”. As argued thus far, jobs-housing balance must be measured based on disaggregated socio-demographic groups, otherwise real jobs-housing balance for service workers might be different from that of transportation workers. Even in “a perfectly balanced situation” where no outbound trips are expected, service workers may have to commute to external zones while transportation workers may not. This is related to intrazonal commuting that may have different rates for service workers and transportation workers. Therefore, in measuring jobs-housing (im)balances, worker types should be taken into account in a
detailed manner. This chapter connects worker heterogeneity and reallocation of jobs and workers simultaneously in the modeling framework.
6.3 An alternative measure of jobs-housing balance

In this section, an alternative measure of jobs-housing balance is presented. Considering worker types, this measure explicitly compares the difference between outbound commuting and inbound commuting, which tends to contribute to jobs-housing imbalance.

6.3.1 Diurnal shift of workers

Based on the difference between daytime and nighttime population, Akkerman (2000) proposes two useful measures that address dynamic aspects of commuting. Population shift ratio \( F \) explains a switch of daytime population and nighttime population (equation 6.1). Commuting exchange ratio \( G \) calculates the ratio of outbound flows to the total daytime workers (equation 6.2). These ratios are as follows:

\[
F_i = \frac{\sum_j X_{lj}}{\sum_l X_{il}}
\]

(6.1)

\[
G_i = \frac{\sum_{j \neq l} X_{lj}}{\sum_l X_{il}}
\]

(6.2)

where

\( X_{lj} \) = total number of outbound commuters from zone \( l \) to \( j \)

\( X_{il} \) = total number of inbound commuters from zone \( i \) to \( l \)

When applied to the journey-to-work matrix, the population shift ratio \( F \) is an equivalent measure of jobs-housing balance. The commuting exchange ratio \( G \) excludes
intrazonal commuting in the numerator and provides a way to look into the dynamic aspect of commuting. Note that G values increase as the percentage of intrazonal commuters increases or that of outbound commuters decrease. Removing unnecessary outbound commuting raises a percentage of intrazonal commuters and this is consistent with a primary goal of jobs-housing balance policies that aims to be closer to the stage of minimum commuting distance (Horner 2002).

6.3.2 A disaggregated measure of worker shift ratio

Adopting Akkerman’s idea of commuting exchange ratio, a disaggregated ratio is presented with some modifications where inbound commuting and occupational groups are explicitly represented (equation 6.3):

\[
R_{ik} = \left( \sum_{j(i \neq l)} X_{ilk} \right) - \left( \sum_{j(j \neq l)} X_{jlk} \right)
\]  

(6.3)

\(R_{ik}\) = Measure of worker shift for \(k^{th}\) occupational group  
\(X_{ilk}\) = Number of inbound work trips to zone \(l\) for \(k^{th}\) occupational group  
\(X_{jlk}\) = Number of outbound work trips from zone \(l\) for \(k^{th}\) occupational group

In equation (6.3), \(R\) measures worker shift for each zone by occupational group. In a case of \(R\) greater than 1, inbound commuting is higher than outbound commuting for \(k^{th}\) occupational group, which implies surplus of jobs in that occupation. If \(R\) is smaller than 1, it indicates surplus of workers or shortage of jobs for \(k^{th}\) occupation. These relationships are clarified as follows where the inbound commuting term is weighted by a certain value of \(\theta\).
\[ R_{lk} = \theta \left( \sum_{i (i \neq l)} X_{iik} \right) - \left( \sum_{j (j \neq l)} X_{ljk} \right) \]  \hspace{1cm} (6.4)

If \( R \) is greater than 0, then

\[ R_{lk} = \theta \left( \sum_{i (i \neq l)} X_{iik} \right) - \left( \sum_{j (j \neq l)} X_{ljk} \right) \geq 0 \]  \hspace{1cm} (6.5)

Hence, \( \theta \) is as follows.

\[ \sum_{j (j \neq l)} X_{ljk} / \sum_{i (i \neq l)} X_{iik} \leq \theta \]  \hspace{1cm} (6.6)

Equation (6.6) is now a ratio of outbound commuting to inbound commuting for zone \( l \) and for the \( k^{th} \) occupation. A weight, \( \theta \), given to inbound commuting term in equation (6.4) can be regarded as an upper bound of workers shift ratio, \( R_{lk} \). If \( \theta = 1 \), inbound commuting is equal to or higher than outbound commuting for zone \( l \), which implies a job-rich situation. The \( \theta \) values can be useful to experiment different policy scenarios ranging from more flexible situations (high \( \theta \) values) to more restricted situations (low \( \theta \) values).
6.3.3 Worker shift ratios in the tri-state area

Tables 6.1 and 6.2 summarize worker shift ratios for each occupation in the tri-state area. Calculations are based on the disaggregated journey-to-work flow obtained from the IM model previously presented in the chapter 4. At the aggregate, worker shift ratios range from 0.66 up to 3.35. However, as expected, those ratios are varied according to occupational groups. Workers in primary economic sectors show the lowest mean (1.06) and median (1.01) average shift ratios. Except in military workers, the highest ratios are found in transportation and production workers (mean 1.40 and median 1.22). An implication is the extent to which workers commute by exchanging workers between zones. Different ranges of worker shift ratio for each occupation verify non-uniform patterns of worker exchange. With given geographic location of residence and jobs, workers in different occupational groups have to make trips either to their county or to external county. Without considering heterogeneity of workers, one is likely to ignore even lower worker exchange ratios shown in table 6.1. Another noticeable trend is that core MSA counties tend to have low worker shift ratios smaller than 1, regardless of occupations (table 6.2). Suburban counties contrast with this tendency where the ratios are mostly higher than 1 except farming, forestry, and fishing occupations.

When jobs-housing balance is discussed, an analyst must consider a possibility of disguised balance caused by an aggregate analysis. Furthermore, the different levels of outbound and inbound commuting should be addressed to maintain or increase intrazonal work trips. These have been concerns of the literature and the following sections propose
linear models in order to predict possible outcomes of commuting pattern through incorporating intrazonal, outbound, and inbound commuting trips. By doing so, one can assess the impacts of worker shift and intrazonal commuting on journey-to-work trip length distribution. As in the previous chapters, all portions are disaggregated by type of workers for the tri-state area.
### Table 6.1 Worker shift ratios (2000)

<table>
<thead>
<tr>
<th>Occupations</th>
<th>Worker shift ratios</th>
<th>County (Lowest)</th>
<th>County (Highest)</th>
<th>Mean</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Range</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All occupations</td>
<td>0.66 – 3.35</td>
<td>Martin, IN</td>
<td>Spencer, KY</td>
<td>1.26</td>
<td>1.20</td>
</tr>
<tr>
<td>Managerial, professional</td>
<td>0.40 – 2.75</td>
<td>Martin, IN</td>
<td>Spencer, KY</td>
<td>1.20</td>
<td>1.14</td>
</tr>
<tr>
<td>Sales</td>
<td>0.68 – 3.95</td>
<td>Mason, KY</td>
<td>Trimble, KY</td>
<td>1.29</td>
<td>1.18</td>
</tr>
<tr>
<td>Service</td>
<td>0.56 – 3.29</td>
<td>Ohio, IN</td>
<td>Trimble, KY</td>
<td>1.18</td>
<td>1.10</td>
</tr>
<tr>
<td>Farming, forestry, fishing</td>
<td>0.41 – 3.90</td>
<td>Knott, KY</td>
<td>Owsley, KY</td>
<td>1.06</td>
<td>1.01</td>
</tr>
<tr>
<td>Transportation, production</td>
<td>0.45 – 6.53</td>
<td>Scott, KY</td>
<td>Robertson, KY</td>
<td>1.40</td>
<td>1.22</td>
</tr>
<tr>
<td>Military</td>
<td>0.00 – 80.21</td>
<td>Belmont, OH</td>
<td>Bullitt, KY</td>
<td>2.52</td>
<td>1.05</td>
</tr>
</tbody>
</table>

### Table 6.2 Worker shift ratios of major urban and suburban counties (2000)

<table>
<thead>
<tr>
<th>Occupations</th>
<th>Cincinnati MSA</th>
<th>Columbus MSA</th>
<th>Indianapolis MSA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Urban</td>
<td>Suburban</td>
<td>Urban</td>
</tr>
<tr>
<td></td>
<td>Hamilton, OH</td>
<td>Campbell, KY</td>
<td>Franklin, OH</td>
</tr>
<tr>
<td>All occupations</td>
<td>0.77</td>
<td>1.59</td>
<td>0.84</td>
</tr>
<tr>
<td>Managerial, professional</td>
<td>0.76</td>
<td>1.60</td>
<td>0.86</td>
</tr>
<tr>
<td>Sales</td>
<td>0.76</td>
<td>1.70</td>
<td>0.85</td>
</tr>
<tr>
<td>Service</td>
<td>0.88</td>
<td>1.26</td>
<td>0.91</td>
</tr>
<tr>
<td>Farming, forestry, fishing</td>
<td>0.91</td>
<td>0.81</td>
<td>0.77</td>
</tr>
<tr>
<td>Transportation, production</td>
<td>0.71</td>
<td>1.72</td>
<td>0.76</td>
</tr>
<tr>
<td>Military</td>
<td>0.73</td>
<td>1.93</td>
<td>0.78</td>
</tr>
</tbody>
</table>
A. Worker shift ratio of service workers (2000)

B. Worker shift ratio of transportation workers (2000)

Figure 6.1 High worker shift ratios (2000)
6.4 Assessing relocation of workers and jobs

The main objective in this section is to develop a modeling framework that relocates residence of workers and their jobs, respectively. Different relocation scenarios are examined under certain conditions that explicitly incorporate intrazonal commuting and worker shift ratio. Extending a linear program developed in chapter 4, additional constraints are added to the models to assess policy scenarios by occupation. In this chapter the most recent 2000 CTPP data are used in the model implementations.

For worker relocation, destination constraints are removed and in a similar fashion origin constraints are removed for job relocation scenarios. With the given aggregate intra-county commuting fixed, several possible scenarios are set by imposing multiple upper bounds. Recall that the upper bounds are explained in terms of $\theta$ in the equation (6.6). Briefly again, $\theta$ can be described as a maximum worker shift ratio of outbound commuting to inbound commuting. As $\theta$ increases, more interactions are likely to occur and commuting lengths tend to increase. Since $\theta$ does not deal with intrazonal commuting, the total number of intrazonal commuters are set to be fixed. Hence, in a particular case of $\theta < 1$, each zone is forced to have a smaller number of outbound commuters than inbound commuters, which implies a job-rich situation.
Origin constrained model (job relocation)

\[ \text{Minimize} \quad T^{\text{MIN}} = \frac{1}{W} \sum_{i} \sum_{j} \sum_{k} X_{ijk} Y_{ij} \] (6.7)

subject to

\[ \sum_{j} X_{ijk} = S_{ik} \quad \forall i, k \] (6.8)

\[ \sum_{j} \sum_{k} X_{ijk} = S_{i} \quad \forall i = 1, \ldots, n + 1 \] (6.9)

\[ \sum_{j} \sum_{k} X_{ijk} = s_{i} \quad \forall i = 1, \ldots, n \] (6.10)

\[ \sum_{i} \sum_{k} X_{ijk} = X_{k} \quad \forall k \] (6.11)

\[ \sum_{i} \sum_{j} X_{ijk} = S_{k} \quad \forall k \] (6.12)

\[ \sum_{k} X_{ijk} = X_{ijk} \quad \forall i = j, j = 1, \ldots, n \] (6.13)

\[ \theta \left( \sum_{i \neq j} \sum_{k} X_{ilk} \right) - \left( \sum_{j \neq i} \sum_{k} X_{ijk} \right) \geq 0 \quad \forall l = 1, \ldots, n + 1 \] (6.14)

\[ X_{ijk} \geq 0 \quad \forall i, j, k \] (6.15)

where

\( \theta \) = Upper bound for the aggregate worker shift ratio

\( X_{ijk} \) = Number of outbound work trips from zone \( l \) to \( j \) for \( k^{th} \) occupational group

\( X_{ilk} \) = Number of inbound work trips to zone \( l \) from \( i \) for \( k^{th} \) occupational group
Destination constrained model (worker relocation)

**Minimize** \[ T^{\text{MIN}} = \frac{1}{W} \sum_{i}^{n+1} \sum_{j}^{n} \sum_{k}^{K} X_{ijk} Y_{ij} \] (6.16)

subject to

\[ \sum_{i}^{n+1} X_{ijk} = D_{jk} \quad \forall j, k \] (6.17)
\[ \sum_{i}^{n+1} \sum_{k}^{K} X_{ijk} = D_{j} \quad \forall j = 1, \ldots, n + 1 \] (6.18)
\[ \sum_{i}^{n} \sum_{k}^{K} X_{ijk} = d_{j} \quad \forall j = 1, \ldots, n \] (6.19)
\[ \sum_{i}^{n+1} \sum_{j}^{n} X_{ijk} = X_{k} \quad \forall k \] (6.20)
\[ \sum_{i}^{n+1} \sum_{j}^{n} X_{ijk} = D_{k} \quad \forall k \] (6.21)

\[ \sum_{k}^{K} X_{ijk} = X_{ijk} \quad \forall i = j (i, j = 1, \ldots, n) \] (6.22)
\[ \theta \left( \sum_{i(\neq j)}^{n} \sum_{k}^{K} X_{ijk} \right) - \left( \sum_{j(\neq i)}^{n} \sum_{k}^{K} X_{ijk} \right) \geq 0 \quad \forall l = 1, \ldots, n + 1 \] (6.23)
\[ X_{ijk} \geq 0 \quad \forall i, j, k \] (6.24)

where

\( \theta = \) Upper bound for the aggregate worker shift ratio
\( X_{ijk} = \) Number of outbound work trips from zone \( l \) to \( j \) for \( k^{th} \) occupational group
\( X_{ik} = \) Number of inbound work trips to zone \( l \) from \( i \) for \( k^{th} \) occupational group
Both models can be regarded as extended versions of the transportation problem presented in chapter 4 (see equation 4.13). Origin constrained model (equation 6.7) holds residential locations of workers and allows jobs to relocate. Destination constrained model (equation 6.16) allows workers’ residences to relocate while location of jobs are fixed. The objective function minimizes average commuting miles (equations 6.7 and 6.16) differentiated by occupation. Note that the original journey-to-work matrix is an \((n \times n)\) matrix and the dimension of the extended O-D matrix is expressed as \((n+1) \times (n+1)\).

For the origin constrained model, constraint (6.8) ensures that the sum of trips originating from \(i\) of type \(k\) matches the observed numbers for each group. Constraints (6.9) and (6.10) ensure that sum of all workers originating from \(i\) should be equal to total number of workers in the extended OD matrix \(((n+1) \times (n+1))\) and the original OD matrix \((n \times n)\), respectively. Constraint (6.11) requires total number of workers for each group should be preserved. Constraint (6.12) preserves information of residential data from CTPP part 1 since the model is constrained with respect to origins. Constraint (6.13) holds the total number of intrazonal commuters. Constraint (6.14) can be described as a policy scenario where a certain upper bound of worker shift ratio, \(\theta\), can be set.

Similarly in the destination constrained model, constraint (6.17) ensures that the sum of trips ending in \(j\) of type \(k\) matches the observed numbers for each group and constraint (6.18) Constraint (6.19) ensure that sum of all workers ending in \(j\) should be equal to total number of workers in the extended OD matrix \(((n+1) \times (n+1))\) and the original OD matrix \((n \times n)\), respectively. Constraint (6.20) is exactly the same as (6.19) to keep total number
of workers in each occupational group. Constraint (6.21) is to preserve employment location data obtained from CTPP part 2. Note that CTPP part 1 data is preserved in the origin constrained model.
6.5 Model application results

Total 10 planning policy scenarios are assessed: 5 for worker relocation and 5 for job relocation (table 6.3). In the worker relocation model, job locations are fixed while the job relocation model preserves residential locations exogenously. For each model, the following 5 scenarios are assessed: (1) all jobs (or workers) are relocated, (2) the aggregate intrazonal commuting preserved, (3) intrazonal commuting preserved and $\theta=3$, (4) intrazonal commuting preserved and $\theta=2$, and (5) intrazonal commuting preserved and $\theta=1$. Details of each model are summarized in table 6.4 below.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Total intrazonal commuting</th>
<th>Worker shift</th>
</tr>
</thead>
<tbody>
<tr>
<td>* Worker relocation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>✗</td>
<td>No 0</td>
</tr>
<tr>
<td>Scenario 1</td>
<td>o</td>
<td>No 0</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>o</td>
<td>$0 = 3$</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>o</td>
<td>$0 = 2$</td>
</tr>
<tr>
<td>Scenario 4</td>
<td>o</td>
<td>$0 = 1$</td>
</tr>
<tr>
<td>** Job relocation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>✗</td>
<td>No 0</td>
</tr>
<tr>
<td>Scenario 5</td>
<td>o</td>
<td>No 0</td>
</tr>
<tr>
<td>Scenario 6</td>
<td>o</td>
<td>$0 = 3$</td>
</tr>
<tr>
<td>Scenario 7</td>
<td>o</td>
<td>$0 = 2$</td>
</tr>
<tr>
<td>Scenario 8</td>
<td>o</td>
<td>$0 = 1$</td>
</tr>
</tbody>
</table>

* Job locations are fixed
** Residential locations are fixed

Table 6.3 Policy scenarios assessed
Table 6.4 presents application results of baseline models for worker relocation and job relocation. Once workers are reallocated, the aggregate minimum commute is 12.01 miles with a 9.36 percent of decrease compared with no relocation situation. Job relocation shows 12.03 miles in minimum commutes for all groups with a 9.23 percent of decrease. However, each occupation varies in its percent reduction in minimum commutes. Worker relocation scenario favors management, professional occupations, sales occupations, and service occupations while job relocation scenario favors the other three occupational groups. Workers in transportation and production occupations most benefit showing 13.10% and 14.05% of reductions in both scenarios of worker and job relocations, respectively. Interestingly, military workers gain even 6.37% increase surpassing predicted actual commuting distance of 15.97 miles. Noting that military workers appear to have the lowest excess commuting of 7.0% in 1990 and 6.1% in 2000 (see table 4.1), their residential distribution may already be close enough to their work places. Other than military workers, service workers appear to have the lowest level of benefits in both scenarios with 5.78% and 4.70% in reductions. According to the job relocation, transportation and production workers whose minimum commutes are the second longest (13.65 miles), are found to have the shortest minimum commutes of 11.97 miles. To the contrary, the worker relocation scenario poses different results. Sales workers show the lowest level of minimum commutes (11.97 miles) followed by service workers (11.89 miles).

These varying levels of minimum commutes justify the needs of the disaggregated approach to jobs-housing balance policies. When each county launches a regional
planning policy, aggregate measures may ignore the hidden variations caused by worker and job characteristics. Recognizing this issue, now the more extended policy scenarios need to be assessed since the results in table 6.4 have presented only two simple relocation scenarios without any considerations of worker shifts and intra-county commuting flows. The basic idea here is to assess hypothetical policies that aim to reduce worker shifts while maintaining the current level of intra-county commuting. In terms of worker shift, \( \theta \) can be regarded as the maximum of the worker shift ratio that describes exchange between outbound commuting and inbound commuting. If \( \theta=1 \) in scenarios 4 and 8, all counties are forced to have a worker shift ratio smaller than or equal to 1, which implies job-rich situations.

Model application results of scenarios 1 through 8 are presented in table 6.5. When workers are relocated, the average minimum commuting increases from 13.83 miles (scenario 1) up to 15.62 miles (scenario 4). Note that scenario 4 is the most aggressive policy scenario where all zones must be job-rich or balanced at the aggregate. At the disaggregated level, each occupation reacts differently to policy scenarios. Once the total intrazonal commuting trips are fixed, the lowest minimum commuting is found in scenario 1 for managerial and professional occupations and primary economic sectors. Scenario 2 favors the rest of occupations. Workers that benefit the most from the scenario 2 are those working in sales occupations, service occupations, transportation and production occupations, and military occupations. Interestingly, the longest commuting is not always found in the scenario 4, the most aggressive policy. Average minimum commuting of managerial and professional workers is the highest in scenario 2.
Transportation and production workers least favor scenario 1 where there is no restriction on the worker shift ratio. As demonstrated here, even if the aggregate minimum commuting increases as policies get more restrictions, each occupation reacts differently according to their residential relocation scenarios.

Job relocation scenarios reveal even more interesting results (table 6.5.B). Surprisingly, scenario 8 where all zones are forced to become job-rich or balanced, transportation and production workers actually achieve the lowest level of commuting (13.55 miles). Note that all other occupations favor either scenario 5 or 6, which have more relaxed settings of worker shift ratio. In addition, transportation and production workers show consistency in reducing their minimum commutes from 16.91 miles down to 13.55 as the upper bounds of total worker shift ratio, $\theta$, gets lower down to 1. While scenario 5 favors workers in 4 out of 6 occupations (managerial and professional occupations, sales occupations, farming, forestry, fishing occupations, and military occupations), scenario 6 is the best for service workers. As mentioned before, transportation and production workers show the lowest minimum commutes in scenario 8 of job relocation policy.

In a comparison of all 8 scenarios, the best planning policy in terms of the lowest minimum commutes can be selected. At the aggregate level, scenario 5 appears to be the most favorable solution for all workers with 13.72 miles of the minimum commuting lengths. However, occupational variations do exist. Scenario 1 appears to be the best for farming, forestry, and fishing occupations. Workers in sales, service, and transportation
and production occupations show the lowest commuting miles in scenario 2. The other 2
groups (managerial and professional occupations and military occupations) make the
shortest minimum commutes under the scenario 4, which is a job relocation scenario.

When jobs or workers are reallocated while holding the intrazonal commuting, it verifies
the non-uniform patterns of minimum commutes under the various policy scenarios. The
most aggressive scenarios where all zones are forced to have a job-rich or balanced
situation, it is not universal that all occupations benefit from that situation. An
implication would be geographic configurations of residence and employment. With the
given locational information, the results show that it is extremely hard to achieve
universal satisfaction in the reduction of minimum commutes. Coupling the results
presented in the previous chapters, this chapter also verifies diverse commuting patterns
by worker types. It is not surprising to expect that workers in different groups seem to
reveal their own travel behavior especially in commuting. Thinking of the primary goal
of jobs-housing balance where the self-containment is emphasized, not all workers
achieve the lowest commutes in one particular policy scenario. As policies get more
aggressive, workers in different types have shown non-uniform or even opposing trend in
their minimum commutes. Commuting patterns are affected by the relationship between
locational factors of their residence and employment. These patterns might be further
extended to other disaggregation dimensions such as industry, gender, or income levels.
<table>
<thead>
<tr>
<th>Occupations</th>
<th>* Predicted commuting miles</th>
<th>Minimum commuting miles (percent reduction in minimum)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>** No relocation</td>
</tr>
<tr>
<td>All occupations</td>
<td>15.81</td>
<td>13.14</td>
</tr>
<tr>
<td>Managerial, professional</td>
<td>15.56</td>
<td>12.98</td>
</tr>
<tr>
<td>Sales</td>
<td>15.60</td>
<td>13.05</td>
</tr>
<tr>
<td>Service</td>
<td>15.50</td>
<td>12.58</td>
</tr>
<tr>
<td>Farming, forestry, fishing</td>
<td>15.35</td>
<td>13.00</td>
</tr>
<tr>
<td>Transportation, production</td>
<td>16.42</td>
<td>13.65</td>
</tr>
<tr>
<td>Military</td>
<td>15.97</td>
<td>14.99</td>
</tr>
</tbody>
</table>

* * Obtained from the IM model in equation (4.7)
** Obtained from the DTP in equation (4.13)
*** Obtained from the policy scenario 1 (See table 6.3)
**** Obtained from the policy scenario 6 (See table 6.3)

Table 6.4 Results of baseline relocation models
### A. Worker relocation

<table>
<thead>
<tr>
<th>Occupations</th>
<th>Minimum commuting miles</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
<th>Scenario 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>No 0</td>
<td>0 = 3</td>
<td>0 = 2</td>
<td>0 = 1</td>
</tr>
<tr>
<td>All occupations</td>
<td></td>
<td>13.83</td>
<td>13.91</td>
<td>14.08</td>
<td>15.62</td>
</tr>
<tr>
<td>Managerial, professional occupations</td>
<td></td>
<td>12.00</td>
<td>16.71</td>
<td>14.48</td>
<td>16.41</td>
</tr>
<tr>
<td>Sales occupations</td>
<td></td>
<td>12.46</td>
<td>12.42</td>
<td>13.62</td>
<td>15.68</td>
</tr>
<tr>
<td>Service occupations</td>
<td></td>
<td>14.00</td>
<td>12.55</td>
<td>15.25</td>
<td>15.97</td>
</tr>
<tr>
<td>Farming, forestry, fishing occupations</td>
<td></td>
<td>12.30</td>
<td>13.36</td>
<td>14.72</td>
<td>18.25</td>
</tr>
<tr>
<td>Transportation, production occupations</td>
<td></td>
<td>16.86</td>
<td>12.99</td>
<td>13.48</td>
<td>14.53</td>
</tr>
<tr>
<td>Military occupations</td>
<td></td>
<td>16.20</td>
<td>15.41</td>
<td>17.57</td>
<td>17.17</td>
</tr>
</tbody>
</table>

### B. Job relocation

<table>
<thead>
<tr>
<th>Occupations</th>
<th>Minimum commuting miles</th>
<th>Scenario 5</th>
<th>Scenario 6</th>
<th>Scenario 7</th>
<th>Scenario 8</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>No 0</td>
<td>0 = 3</td>
<td>0 = 2</td>
<td>0 = 1</td>
</tr>
<tr>
<td>Managerial, professional occupations</td>
<td></td>
<td>11.92</td>
<td>13.69</td>
<td>13.96</td>
<td>14.45</td>
</tr>
<tr>
<td>Sales occupations</td>
<td></td>
<td>12.52</td>
<td>12.83</td>
<td>13.25</td>
<td>13.73</td>
</tr>
<tr>
<td>Service occupations</td>
<td></td>
<td>13.13</td>
<td>12.87</td>
<td>13.85</td>
<td>14.27</td>
</tr>
<tr>
<td>Farming, forestry, fishing occupations</td>
<td></td>
<td>13.40</td>
<td>14.64</td>
<td>13.86</td>
<td>16.18</td>
</tr>
<tr>
<td>Transportation, production occupations</td>
<td></td>
<td>16.91</td>
<td>15.38</td>
<td>14.01</td>
<td>13.55</td>
</tr>
<tr>
<td>Military occupations</td>
<td></td>
<td>13.98</td>
<td>14.06</td>
<td>14.50</td>
<td>18.00</td>
</tr>
</tbody>
</table>

* Total number of intrazonal trips is fixed.

Table 6.5 Model application results for 8 policy scenarios
6.6 Discussion

This chapter has assessed multiple policy scenarios focusing on diurnal worker shifts and intrazonal commuting both of which are critical to the concept of jobs-housing balance. The planning scenarios summarized in tables 6.1 through 6.5 suggest that worker shift ratio, the ratio of outbound commuting to inbound commuting have impacts on the minimum commutes both at the aggregated and the disaggregated level by worker type. As expected the average minimum commutes at the aggregated level have increased as policies become aggressive or more restricted in terms of reducing diurnal worker shifts. However, varying levels of minimum commutes are found for each occupation. Overall, job relocation scenarios (scenario 5) appear to be the most effective to workers in managerial and professional occupations and military occupations. Residential relocation policies favor the rest of groups with different preferences of worker shift ratios. Sales and primary sector workers favor scenario 1 with no restrictions of worker shift while service and transportation workers most benefit from the scenario 2 when a certain worker shift ratio is imposed. Such a experimental study provides a valuable view on how much exchange of workers may contribute to the commuting pattern. As argued throughout this dissertation, total worker flow may disguise occupational variations in commuting behavior. The results suggest that worker and job characteristics should be carefully taken into account since a policy favorable to a certain group of workers may actually have negative impacts on other groups of workers.

Keeping this in mind, the disaggregated analysis presented here might be a big step towards assessing jobs-housing balance policies. Jobs-housing balance may appear to be
a simple concept, however, it embraces a variety of complicated concerns. For example, self-containment by increasing intrazonal commuting may help achieve mixed land use pattern that encourages workers live and work in the same zone (Cervero 1989). In addition, reductions in high worker shifts may improve jobs-housing balance. Jobs-housing balance now must be extended to “balance for which type of workers?” In the planning context, a specific policy should be assessed based on its future impacts on commuting pattern because there may be trade-offs between occupational groups. As presented in this chapter (see tables 6.1 and 6.2), residential development may favor sales workers while other groups have opposing preferences. Another implication is the complexity of spatial structure. When spatial structure is defined by given residential and employment locations, it may not be identical by region, by worker type, and by industry. This dissertation thus far has discussed one aspect of disaggregation by worker type, as a benchmark approach to provide future possibilities of disaggregation. The intent is to understand and verify variations in excess commuting and jobs-housing balance according to the type of workers. All analysis chapters from chapter 4 through this chapter 6 verify that those variations do exist.
CHAPTER 7 CONCLUSIONS

Much of the analysis to date on the topics of excess commuting, jobs-housing balance, and accessibility deals only with total commuting flow, undifferentiating worker and job characteristics. Measures based on undifferentiated worker types may produce misleading results because all workers, even if they are in different jobs, are assumed to be homogeneous. This dissertation has investigated the importance of disaggregated journey-to-work data by type of occupation and presented a set of trip distribution models, as a benchmark approach, that break total commuting flow down to individual flows differentiated by occupation. The intent is to understand and verify variations in excess commuting, jobs-housing balance, and accessibility over the ten-year period.

All analysis chapters from chapter 4 through chapter 6, have verified that those variations do exist. Analyses have been conducted at the county level in the tri-state area of Indiana, Kentucky, and Ohio. Uniqueness in this dissertation is to capture inter-state commuting flow, particularly in Cincinnati and Louisville MSAs that consist of counties across two or more states. This dissertation has emphasized regional contexts under the notion that spatial structure, defined by residential and employment locations, may not be identical across regions. Census Transportation Planning Package (CTPP) has been extensively
used as the primary data source. CTPP data sets in two census years, 1990 and 2000, have been used to provide a comparative view.

In chapter 4, two trip distribution models are applied. The information minimization model predicts actual trip lengths by occupation and the linear program estimates minimum commutes for each occupational group. From the data manipulation to model implementation, the models consistently control for total worker flow and produce additive journey-to-work flows. Empirical results verify the existence of varying trip length distributions and non-uniform levels of excess commuting and jobs-housing balance for each occupation both in 1990 and 2000. By presenting predicted and optimized worker flow patterns this study can answer the question, “where are workers going for the work?” Knowing exactly where workers could be redistributed provides useful information for urban transport policies. Since excess commuting is a measure of potential commute reduction, we can evaluate where more jobs need to be created or relocated and how many workers are contributing to excess commuting.

In chapter 5, residential and employment accessibility are visualized and analyzed using the origin and destination balancing factors from the IM model developed in chapter 4. These origin and destination specific balancing factors are useful as an extended and disaggregated accessibility measure to explore employment centers and residential areas. Occupational characteristics are explicitly addressed and temporal changes over the ten-year period are discussed. According to the empirical results, major urban counties are
ranked high in both employment and residential centers while suburban counties in or close to major MSAs have gained highest accessibility increases between 1990 and 2000.

In chapter 6, multiple policy scenarios are assessed focusing on diurnal worker shifts and intrazonal commuting. Total 10 scenarios have been assessed: 5 scenarios under the worker relocation and the other 5 under the job relocation. Overall, empirical results show that the worker shift ratio has impacts on the minimum commutes both at the aggregated and the disaggregated level by worker type. The average minimum commutes at the aggregated level have increased as policies become aggressive or more restricted in terms of reducing diurnal worker shifts. However, varying levels of minimum commutes are found for each occupation. Such an experimental study provides a valuable view on the dynamics of worker exchange as inbound and outbound commuting flows may cost longer commuting. Model application results imply that worker and job characteristics should be carefully considered in a policy because a certain group of workers benefit at the expense of the other groups of workers.

This dissertation is anticipated to have contributions to commuting research and opens up future research directions. First, the scope of the disaggregation can be extended to other detailed groups beyond occupational types. Disaggregation models can be applied for other targets such as different types of industry, household structure, income level, ethnic background, education level, transportation mode, and gender. By doing so, one can identify different pictures of spatial structure in greater detail. Second, a comparative work across multiple urban settings seems to be an obvious extension, and may be highly
instructive in cities that have special contextual situations (multiple nuclei, growth control, above-average transit use, or special physical constraints etc.). Third, estimating the viability of particular land use sub-markets can be aided. For example, office space is potentially more valuable when it is placed accessible to workers who can benefit from shorter commutes. From a policy standpoint, the distribution of trip makers on a particular purpose is heavily dependent on the supply of workspaces. One key to understanding the market for office space is in knowing which locations are accessible to suitable labor pools. Fourth, this research has experimented several policy scenarios considering intrazonal commuting and worker shifts. Building upon the efforts to assess job and worker relocation policies in the past, this research incorporates the relationship between inbound and outbound commuting in the relocation models to assess possible policy outcomes to each occupational group. It is found that each occupation reacts differently to policy scenarios. While the aggregate minimum commuting miles may increase as more restriction is given in the policy, each occupation favors different policies. It is also found that reducing the worker shift ratio of a zone may improve jobs-housing balance at the expense of commuting length.

This dissertation has addressed implications of disaggregated commuting data as a way to provide better understanding of the relationships between commuting and spatial structure. As a benchmark approach, disaggregation according to worker type has been explicitly addressed. A set of trip distribution models has been developed to predict actual commutes and minimum commutes at the county level in the tri-state area. As expected, occupational variations are identified with no exceptions. Now it becomes
evident that ignoring worker or job heterogeneity may lead to disguising results since all workers cannot be the same. The disaggregated analysis presented here might be a big step towards assessing planning policies. In the planning context, the jobs-housing balance now must be extended to “balance for a certain type of workers”. A specific policy should be assessed based on its future impacts on commuting pattern because there may be trade-offs between occupational groups. Although the zonal self-containment can be achieved by increasing intrazonal commuting through concentrated mixed land use patterns, one policy may not bring positive outcomes to all worker groups.

Models, empirical results, and findings in this research should be treated as a continuing effort to understand complicated aspects of people’s interaction as a form of commuting. This dissertation has opened a wide range of possibilities for studies of detailed spatial structure, and has provided the tools that have practical use as well as potential for more sophisticated understanding of commuting patterns.
BIBLIOGRAPHY


