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# Temporal Trends of Intraurban Commuting in Baton Rouge 1990-2010

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TEMPORAL TRENDS OF INTRAURBAN COMMUTING IN BATON ROUGE 1990-2010

A Dissertation

Submitted to the Graduate Faculty of the  
Louisiana State University and  
Agricultural and Mechanical College  
in partial fulfillment of the  
requirements for the degree of  
Doctor of Philosophy

in

The Department of Geography and Anthropology

by

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August 2016

In loving memory of my maternal grandmother, Peiyu Cong (1935 - 2003)

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## **ABSTRACT**

Based on the CTPP data 1990-2010, this research analyzes the temporal variability of commuting patterns and efficiency (in both distance and time) in Baton Rouge, Louisiana. It proposes a simulation-based method to measure commuting by simulating individual resident workers, jobs, and trips between them, in order to mitigate the aggregation error and scale effect that are commonly encountered in existing studies. Specifically, the Monte Carlo simulation approach is adopted to simulate individual resident workers and jobs that were consistent with their spatial distributions across the areal unit (e.g., census tract), and then simulate individual trips that were proportional to the existing journey-to-work trip flows. The results indicate that average commute distance kept climbing between 1990 and 2010, whereas average commute time increased between 1990 and 2000 but then slightly dropped toward 2010.

As commuting is a trip linking one's residence to employment, this research follows the long tradition of using the urban land use pattern, namely the spatial separation between residential housing and job location, to explain the observed commuting pattern. Three land use measures are used: distance from the CBD, jobs to resident workers ratio, and a gravity-based job proximity index. The research finds that these land use measures remained a good predictor of commuting pattern in Baton Rouge over time, and the best model explained up to 90 percent of mean commute distance and about 30 percent of mean commute time.

Furthermore, nonspatial factors such as a worker's socioeconomic attributes also influence commuting. Foremost, income plays an important role in one's residential choices and thus commuting. This research focuses on the role of wage rates of resident workers in commuting pattern. It is reported that commuting behaviors varied across areas of different wage rates, captured by a convex shape. Initially workers living in more affluent neighborhoods tended to



commute more, but those in areas with the highest wage rates retreated for less commuting. This trend remained relatively stable over time.

Wasteful (excess) commuting is also examined as the overall commuting efficiency metric for the study area. Wasteful commuting is measured as the proportion of actual commute that is over minimum (optimal) commute when assuming that people could freely swap their homes and jobs in a city. This research identifies two contributors resulting in the miscalculation of wasteful commuting: reporting errors and the use of aggregate zonal data. The former tended to overstate the actual commuting length and led to overestimate wasteful commuting; and the latter (especially the use of large areal unit) led to underestimate wasteful commuting. This research indicates that the percentage of wasteful commuting increased significantly between 1990 and 2000 and stabilized afterward.

## **CHAPTER 1. INTRODUCTION**

Commuting, a human mobility behavior for employed individuals, occurs on a daily basis by multiple transportation modes (e.g., drove-alone, carpool, public transit, bicycle and walk). By linking home (residential areas) to employment (commercial, industrial and other land uses), commuting is a key factor in affecting land use patterns (AASHTO, 2013). As population and jobs become increasingly decentralized, commuters are traveling longer (both length and duration) than ever before (Gordon et al., 2004). For example, the average commute time by the U.S. workers was 24 minutes on their one-way trips to work in 2003, and increased to 25.1 minutes in 2009 (McKenzie and Rapino, 2011). According to National Household Travel Survey, one-out-of-twelve U.S. workers spent an hour or more in their one-way commute trips in 2001, compared to one-out-of-twenty in 1995. This is especially worse in large cities where one-out-of-ten workers experienced the same amount of time to commute on average less than 38 miles (<http://nhts.ornl.gov/briefs/Commuting%20for%20Life.pdf>, p.1). In the meantime, an increasing number of commuters is choosing the drove-alone mode especially during the job decentralization era when inter-suburb and reverse commuting are more common. For instance, 75.5 percent of the U.S. workers drove alone to jobs in 2008, and the ratio increased to 76.1 percent in 2009 (Fields and Jiles, 2009).

Given the increasingly longer length and duration and the dominantly auto-dependent travel mode, commuting is strongly connected with some practical issues on which many public policies concentrate (Sultana and Weber, 2014). It is a major contributor to traffic congestion, air pollution and greenhouse gas emissions. Even though commuting represents only 20-25 percent share of all-purpose trips in the United States (Sultana, 2002; Horner, 2004), it results in two of the most congested periods in a day and establishes the major transportation infrastructure and service

needs. For example, the average commute speed declined about 10 percent in midsize metropolitan areas from 1990 to 2009 (<http://nhts.ornl.gov/2009/pub/stt.pdf>, p.49). In line with the worsened traffic congestion, commuters are spending more time in their daily commute trips all across the United States. The Texas Transportation Institute (TTI) estimated that in 2010 the average commuter spent an additional 34 hours annually and wasted 14 gallons of gas sitting in traffic (TTI, 2011). In addition, among all economic sectors, transportation (including commuting) is the “second-largest contributor to total U.S. emissions” (next to industry) but with the fastest growth rate, especially given the fact that the growth of urban travel has significantly outpaced that of population in the United States during the past three decades ([www.state.gov/documents/organization/140636.pdf](http://www.state.gov/documents/organization/140636.pdf), p.36). According to Table VM-202 in Highway Statistics (U.S. DOT/FHWA, 2012) and Table 7 in Statistical Abstract of the United States (U.S. Census Bureau, 2012), the Vehicle Miles Travelled (VMT) in the U.S. urban areas has increased by 133 percent from 1980 to 2012 while the population increased by 36 percent during the same period. Therefore, efforts focused on studying the urban commuting behavior, for example, understanding the temporal change of commuting and its underlying causes is a step toward the larger goals of traffic congestion mitigation and carbon emission control.

Commuting has been widely studied in previous research, such as investigating the influences of urban form, wasteful commute, jobs-housing balance, and accessibility on commuting pattern (Cervero, 1989; Horner, 2004; Sultana, 2002; Sultana and Weber, 2014; Wang, 2001). However, most studies are affected by aggregation error (e.g., measuring commuting distance by a zonal centroid-to-centroid distance) and scale effect (e.g., inconsistent analysis results are obtained due to different unit scales and unit zone definitions). More accurate measures of commute remain very much needed.

The very focus of this dissertation is to detect and explain the temporal trends of intraurban commuting pattern (measured by both commuting distance and time) in Baton Rouge, Louisiana between 1990 and 2010. Specifically, this dissertation aims at:

- designing a simulation-based approach for more accurate and reliable measures of commuting length so as to mitigate the aforementioned issues that have been central to the study of commuting;
- applying the proposed approach to detecting the intraurban commuting pattern (in both distance and time) in Baton Rouge, Louisiana over time (between 1990 and 2010);
- investigating how a spatial factor—land use—influences the discovered commuting pattern;
- examining the impact of a nonspatial factor—wage rate—on the detected commuting pattern;
- measuring commuting efficiency, i.e., wasteful commuting behavior and its temporal trends.

The following chapters discuss the above analyses. Chapter 2 reviews existing commuting studies. For example, it groups the literature into several categories: measures of commuting length, explaining commuting by spatial factors, explaining commuting by nonspatial factors, and wasteful commuting.

Chapter 3 describes the study area and data sources. This dissertation selects East Baton Rouge Parish in Louisiana as the study area. Major data sources used in this dissertation include census unit boundary (e.g., census tract) and road network data in a GIS format (e.g., shapefile), as well as commuting and socioeconomic data (e.g., number of commuters and a tract's mean wage rate) in ASCII format (e.g., MS Excel) from the U.S. Census Bureau.

Chapter 4 explains the proposed simulation-based approach designed to measure commuting length. Specifically, it first gives a brief introduction to this method, and then illustrates the principle and process to simulate resident workers, jobs and commuting trips between them.

Chapter 5 detects the temporal trends of commuting pattern in both distance and time and then investigates the relationship between commuting and a spatial factor—land use. The land use layout is characterized by three indices—distance from CBD, jobs-housing balance ratio, and proximity to jobs.

Chapter 6, on the other hand, examines the impact of a nonspatial factor—wage rate—on shaping the commuting pattern. For example, it inspects the commuting pattern first by neighborhood's average wage and then by distribution of wage groups across neighborhoods.

Chapter 7 measures the commuting efficiency—wasteful commuting behavior as well as its change over time. It presents two analyses at an aggregated level and at the individual level, respectively, and then compares the results.

Chapter 8 discusses the results and conclusions reached by the preceding chapters, as well as describes the contributions, limitations and future steps of this dissertation. Followed are the references used throughout this dissertation and the author's vita.

## **CHAPTER 2. LITERATURE REVIEW**

Commuting has a dynamic nature, in other words, it can vary in different times, places, and socio-economic groups. For example, commuting around 8am could be more remarkable than around 10am; commuting originating from places far away from downtown area could be dissimilar to places near CBD; and commuting behavior may not be the same for White vs. African American (or male vs. female). Given its important role in daily life and the complex nature, this subject has received considerable attention in the literature. Studies have been conducted to model and explain the commuting pattern in order to gain better understanding of human mobility, and can be summarized into the following aspects.

### 2.1 MEASURES OF COMMUTING LENGTH

The topic of measuring commuting length deserves some discussion, as it is the core for this research. In the commuting literature, time is oftentimes utilized to analyze the spatial separation between home and job sites, as it is directly available from survey data (e.g., CTPP); however, mileage could provide a more consistent measure of commuting length (Sultana and Weber, 2007) and is not studied as much as time. Existing literature used a simple zonal centroid-to-centroid approach to reconstruct Euclidean distance (Gera, 1979; Hamilton, 1982; Levinson and Kumar, 1994; Levinson, 1998; Horner and Murray, 2002; Clark et al., 2003; Wang, 2003; Kim, 2008). However, some argued that the centroid-to-centroid straightline distance measure is not close to actual commute distance as it lacks the consideration of real transportation network, and thus preferred the network distance measure. Specifically, the network distance estimated the commuting distance as the shortest-time distance between two zone centroids using GIS network modeling techniques (White, 1988; Levinson and Kumar, 1994; Cervero and Wu, 1998; Wang, 2000; Wang, 2001; Horner, 2002; Yang, 2008). This would necessarily assume that commuters

are utility-maximizers, in other words, they will choose the shortest route to work; while not always true, it is a much closer representation of actual commute distance, especially compared with the Euclidean distance. However, this distance measure, though more complex, could underestimate the actual distance, as it is still a measure between zone centroids where all people are assumed to start and end a journey. Such an approach could bias the estimate particularly in large zones and also by omitting intrazonal distance. Hewko et al. (2002) noted, aggregation error resulted from using a centroid to represent a neighborhood in distance measure, would be significant for analyses using more aggregated units such as census tracts; additionally, facilities under investigation that are plentiful and more spatially concentrated (e.g., jobs) would cause more errors in their analysis of neighborhood spatial accessibility. For this reason, Horner and Schleith (2012) used a small analysis unit such as census block to reduce such aggregation error. Commuting data at the block level, however, are not widely available for most cities in the United States. Different unit scales and unit zone definitions cause inconsistency in analysis results, particularly common in comparison analysis over time, and thus lead to the MAUP (Niedzielski et al., 2013). Some recent studies have shown great promise in using Global Positioning System data and activity-travel surveys of individual trip makers in commuting studies (Shen, Kwan, and Chai, 2013; Kwan and Kotsev, 2015). Such data, however, might not be representative of all commuters and are also not universally available. More accessible and accurate measures of commute length remain very much needed.

One possible way is to use simulation techniques for commute length measures. This research proposes to apply the Monte Carlo simulation method; specifically, it simulates individual resident workers and jobs that were consistent with their spatial distributions across the areal unit (e.g., census tract), and then simulates individual trips that were proportional to the existing journey-to-

work trip flows. In this way, aggregated trips extracted from survey data (e.g., CTPP) are disaggregated into individual level, free from aggregation error and scale effect.

The Monte Carlo simulation technique is widely used in spatial analysis. Here, I briefly discuss its applications in spatial analysis, e.g., spatial data disaggregation and statistical testing. More details regarding this technique and its principle are described in Chapter 4.

Spatial data often come as aggregated data in various areal units (sometime large areas) for various reasons. One likely cause is the concern of geo-privacy. Others include administrative convenience, integration of various data sources and limited data storage space, etc. Several problems are associated with analysis of aggregated data such as

- modifiable areal unit problem (MAUP), i.e., instability of research results when data of different areal units are used,
- ecological fallacy, when one attempts to infer individual behavior from data of aggregate areal units (Robinson, 1950), and
- loss of spatial accuracy when representing areas by their centroids in distance measures.

Therefore, it is desirable to disaggregate data in area units to individual points in some studies. For example, Watanatada and Ben-Akiva (1979) used the Monte Carlo technique to simulate representative individuals distributed in an urban area in order to estimate travel demand for policy analysis. Wegener (1985) designed a Monte Carlo based housing market model to analyze location decisions of industry and households, corresponding migration and travel patterns, and related public programs and policies. Poulter (1998) employed the method to assess uncertainty in environmental risk assessment and discussed some policy questions related to this sophisticated technique. Luo et al. (2010) used it to randomly disaggregate cancer cases from the zip code level to census blocks in proportion to the age-race composition of block population, and examined



implications of spatial aggregation error in public health research. Gao et al. (2013) used it to simulate trips proportionally to mobile phone Erlang values and to predict traffic-flow distributions by accounting for the distance decay rule.

Another popular application of Monte Carlo simulation in spatial analysis is to test statistical hypotheses using randomization tests. The tradition can be traced back to the seminal work by Fisher (1935). In essence, it returns test statistics by comparing observed data to random samples that are generated under a hypothesis being studied, and the size of the random samples depends on the significance level chosen for the test. A major advantage of Monte Carlo testing is that investigators could use flexible informative statistics rather than a fixed, known distribution theory. Besag and Diggle (1977) described some simple Monte Carlo significance tests in analysis of spatial data including point patterns, pattern similarity, and space-time interaction. Clifford et al. (1989) used a Monte Carlo simulation technique to assess statistical tests for the correlation coefficient or the covariance between two spatial processes in spatial autocorrelation. Anselin (1995) used Monte Carlo randomization in the design of statistical significance tests for global and local spatial autocorrelation indices. Shi (2009) proposed a Monte Carlo-based approach to test whether the spatial pattern of actual cancer incidences is statistically significant by computing p-values based on hundreds of randomized cancer distribution patterns.

## 2.2 EXPLAINING COMMUTING BY SPATIAL FACTORS

There has been a sustained interest in (and debate of) explaining intraurban variation of commuting by land use pattern (Giuliano and Small, 1993; Wang, 2000; Sultana, 2002; Horner, 2004; Horner, 2007; Horner and Schleith, 2012). In essence, commuting is for a worker to overcome the spatial barrier from home to workplace, and therefore explanation of commuting naturally begins with a focus on the spatial separation of resident (population) and employment

locations. Past attempts include modeling how far a residential location is from a job concentration area (e.g., CBD) or from the overall job market, or measuring the need of commuting beyond a local area (e.g., captured by the jobs-housing balance ratio). For example, job-housing imbalance would be related to longer commute and the increasing traffic congestion. An area would be considered job-housing imbalance when the number of resident workers differ considerably from the number of jobs (Giuliano and Small, 1993). Cervero (1989) made an attempt based on data in the San Francisco Bay Area and other U.S. cities, and found that areas with severe job-housing imbalance were associated with longer commutes. On the contrary, urban areas with balanced jobs and housing (i.e., integrated residential and employment locations) would promote less commuting. Wang (2000) found that mean commuting distance was more sensitive to job-housing imbalance than mean commuting time. Sultana (2002) investigated this relationship of commuting pattern and job/housing imbalance in the Atlanta metropolitan area based on 1990 CTPP (Census Transportation Planning Package) data and also supported the determining role of job/housing imbalance in causing long commuting. Horner (2002) studied 26 U.S. cities and reached that commuting lengths were well correlated with jobs-housing balance. A few recent studies examined the temporal change in commuting patterns and connected it with land use patterns. For example, Horner (2007) explained the spatial-temporal pattern of intraurban commuting (mileage and multiple commuting efficiency metrics) from the jobs-housing balance perspective in Tallahassee, Florida, from 1990 to 2000. Similarly, Chen, Zhan, and Wu (2010) investigated the change in commuting patterns from analyzing the residential and employment distributions in central Texas between 1990 and 2000.

Policies advocating some land use metrics such as jobs-housing differ from other attempts on commuting in that they are explicitly focused on the spatial perspective, and this lays such

approaches open to criticisms, however (Horner, 2004). For instance, Giuliano and Small (1993) found that the relationship between commuting times and jobs-housing balance ratio was significantly small in Los Angeles area. Peng (1997) concluded that such relationship between commuting and jobs-housing was clear only in cases where jobs and housing were extremely unbalanced. Similarly, Cervero (1996) supported the above finding but defined it more specifically that only in places where job creation was far more than residential location production did commutes change. Levinson (1998) also investigated such plausible relationship and found moderate support in Washington, DC. Specifically, he argued that personal choice would play a more significant role in affecting housing/employment decisions than jobs-housing balance, and therefore, policies aiming at improving jobs-housing balance in order to alleviate traffic congestion would not perform well.

In the meantime, a debate focusing on the relationship between job decentralization and commuting was also recognized. As discovered by Gordon et al. (1991), the average commuting time in the 20 largest metropolitan areas was found to remain stable overtime, albeit the increase in traffic congestion in cities. Based on the tradeoff assumption in the theoretical urban economic model, a more decentralized city would have more workers migrating to locations near employment sub-centers to minimize their commuting costs, and thus give rise to shorter commuting time (Gordon et al., 1989b). This is consistent with Downs (1992), who argued that the decentralization of suburban job sites would decrease commuting. To better explain the above commuting paradox, a co-location theory was proposed, which states that workers would change their residence or jobs in order to adapt to the worsening traffic congestion (Gordon et al., 1991). Levinson and Kumar (1994) supported this theory based on their findings of stable commuting time in Washington metropolitan region, and further defined those workers as rational locators.

Empirical evidence to this pattern is also found in Crane and Chatman (2003) and Sultana and Weber (2007) that job decentralization would encourage shorter commuting distance.

However, there are some studies that contradicted the co-location theory. For example, Cervero and Wu (1998) found that the rapid job decentralization in San Francisco Bay Area, on the contrary, led to the rise in average commuting distance and time between 1980 and 1990. This opposing finding was also detected in Levinson and Wu (2005). In addition to that, they also found that the commuting time could vary among different metropolitan structures. Aguilera (2005) also discovered the same changing pattern in three biggest French metropolitan areas and thus disputed the co-location theory.

### 2.3 EXPLAINING COMMUTING BY NONSPATIAL FACTORS

There are also nonspatial factors that lead to more commuting beyond what can be predicted by the land use pattern. Some research studies tried to understand commuting based on the classic urban economic model (Muth, 1969; Mills, 1972), which suggests that the tradeoff between commuting and housing dictates a household's residential choice. Specifically, it assumes that workers would move farther away from CBD and thus commute longer to trade for better housing. Zax and Kain (1991) investigated the impact of commute distance on quit and move behaviors based on the residential choice theory. They found that long commutes resulted from the tradeoff between commuting cost and housing consumption would encourage quits and discourage moves, in metropolitan areas with negative wage and housing price gradients. Dubin (1991) found that workers prefer less commuting in terms of time, and would use suburbanization to shorten their commute time, consistent with the prediction of monocentric model that firm decentralization would reduce total commuting.

Arguably, it becomes increasingly difficult to apply this simplistic urban model to current

urban structures, particularly, large metropolitan areas, where job decentralization becomes a norm (Horner, 2004). This assumption regarding income and housing may still be applicable to urban areas where CBD dominates the job market, however. Given the same income level, a worker living farther away from the CBD commutes longer and is compensated by more spacious housing, and this leads to a decentralized housing development pattern. Such pattern is especially common in the United States, where people are enjoying increased mobility and are capable of living where they want to, without compromising their opportunity in engaging life activities (Horner, 2004). However, as residents differ a great deal in income, how does income influence one's tolerance of commute and desire of housing space? For example, low-wage workers are reported to spend a much higher proportion of their income on commuting (6.1 percent) than other workers (3.8 percent); furthermore, the working poor who rent spend a greater portion of their income on combined costs of commuting and housing (32.4 percent) than other workers (19.7 percent) (Roberto, 2008). Low-wage workers also have significantly lower vehicle ownership than others (Lowe and Marmol, 2013), and are thus more likely to use slower transportation modes such as public transit, carpool, bicycle and walk than their high-wage counterparts (Ross and Svajlenka, 2012; McKenzie, 2014). To this end, higher-wage workers may generally commute longer than lower-wage workers because of their better mobility and economic conditions. Lack of access to data of individual commuters, particularly quality data over a long time period, prevents us from addressing the question directly. Nevertheless, analysis of commuting variability by neighborhood income levels may still shed light on the issue (Wang, 2003). Gordon et al. (1989c) investigated the relationship between income and commuting and argued that commuting times would increase with income. Rosenbloom and Burns (1993) discovered the same pattern between commuting and income; as income increases, commuting distance would increase for both men and women

workers. Wang (2003) measured commuting lengths (in both distance and time) for different wage groups in Cleveland and found that compared to time, commuting distance was more sensitive to wage in a way that wealthier workers commuted more than lower wage workers, but the wealthiest wage group shortened commute slightly. A recent work by Horner and Schleith (2012) investigated the commuting pattern by three income groups (i.e., low, medium, and high) based on their monthly income, and found that the average observed and minimum commute became lengthier as the income increased. More detailed income subgroups may help detect more hidden pattern in terms of income and commuting length, however.

There are also other nonspatial factors commonly investigated in the literature besides income. For instance, people of a racial-ethnic minority (by extension any disadvantaged groups) may commute more than their white counterpart, commonly-known as “spatial mismatch” (Kain, 1968); and multiple-worker household tend to commute more because of difficulty of coordinating multiple commute trips. Gera (1979) found that age was related to commuting behavior that commuting distance tended to decrease with age. Gordon et al. (1989a) recognized that women have significantly shorter commutes than male. Gordon et al. (1989c) suspected that commuting would be related with occupation; and higher share of industrial employment would offer more opportunities for shorter commuting time. They also examined transportation modes and found that carpools would result in longer commuting time than drove-alone. Wang (2001) considered workers’ socio-demographic characteristics (e.g., race, gender, home-ownership status and education) in his model and found significant relationship between some variables (e.g., race and gender) and commuting. Sultana and Weber (2007) also showed the promise of using workers’ socioeconomic characteristics to explain commuting patterns. In short, as discussed above, commuting may be explained by where they are and by who they are (Wang 2003).

## 2.4 WASTEFUL COMMUTING

Wasteful or excess commuting is another line of research closely related to the paradigm of interrelatedness between land use and commuting, and reflects the overall commuting efficiency in a city. It is measured as the proportion of actual commute that is over minimum (optimal or required) commute when assuming that people could freely swap their homes and jobs in a city (Hamilton, 1982; White, 1988; Horner and Murray, 2002). Instead of focusing on the variation of commuting across areas, it highlights how much overall commuting could be reduced based on the above assumption. In other words, the concept captures the potential (or lack of potential) for a city to optimize commuting without altering the existing land use, and to some extent, reflects efficiency in its land use layout. Based on the definition of the optimal commute, other commuting efficiency metrics were then designed. Horner (2002) proposed the theoretical maximum commute to represent the most inefficient or costly regional commuting flow pattern given the existing spatial arrangement of workers and jobs. He then defined a metric commuting range as the difference between theoretical maximum and minimum commute to reveal how much commuting flexibility or capacity is available for commuting. Another metric the capacity consumed statistic is expressed as the difference between actual and optimal commute, divided by the commuting range; and it indicates how much of a region's commuting potential (or capacity) has been utilized (accounted for by the observed commute). Both metrics above provide alternative views of a region's commuting efficiency in comparison to wasteful commuting.

Besides the minimum and maximum commute, a theoretical random commute was then put forward (Charron, 2007; Yang and Ferreira, 2008; Layman and Horner, 2010; Murphy and Killen, 2011), sitting between the lowest and highest theoretical commuting cost scenarios. Alternatively, it represents a commute pattern in which workers are not sensitive to commuting costs in making

location decisions. Put it in another way, it corresponds to a spatial interaction model with no distance decay effect, i.e., no impact of travel cost (Niedzielski et al., 2013). Based upon theoretical random commute, another policy-relevant commuting efficiency metric named commuting economy is provided. Similar to the capacity consumed statistic, commuting economy also tackles the association between commuting potential and practical utilization. Carried out differently, the theoretical random commute is considered a more realistic representation of the commuting upper bound than maximum commute in a region.

Though all the above metrics offer insight into a region's commuting efficiency, this research is specifically interested in wasteful commuting that tackles the connection between theoretical minimum commute and actual commute, given its fundamental importance in the literature of commuting efficiency, its implication related to journey to work pattern, land use, and the spatial separation of home and jobs, its policy-related role in benchmarking urban travel efficiency (Horner, 2004; Horner and Schleith, 2012), and, most importantly, its methodological issues that remain unresolved (Horner and Murray, 2002; Fan et al., 2011; Niedzielski et al., 2013).

The concept of wasteful commuting was first proposed by Hamilton (1982), as he was to examine if the classical urban economic model would perform a good job in predicting the mean commute length in a city. Hamilton assumed that both population and employment densities decline exponentially with distance from the city center, and the latter have a steeper gradient than the former. Assuming that residents could freely swap houses, the optimal (minimal) commuting pattern is that people always commute toward the city center and the trips end at the nearest jobs. As a result, the average minimal commute is the difference in average distances of population and employment from the city center. Surprisingly, he found that actual commute was about 87 percent excess in comparison to the optimal in 14 U.S. cities. White (1988) argued that the urban commute



optimization should be constrained to the existing spatial distribution of homes and jobs and the road network, and formulated the optimal commuting pattern by a simple Linear Programming (LP) approach. White's model returned only 11 percent wasteful commuting for the same study areas used by Hamilton. The large gap in the results by Hamilton and White has led to a sustained debate on how to accurately measure wasteful commuting, and generated a large volume of literature from multiple disciplines.

Some attributed the discrepancy to the scale (zonal) effect. Hamilton (1989) cautioned researchers of assuming an optimal intrazonal commute, and pointed out that a larger zone size might lead to less wasteful commuting. In practice, the LP result usually yields a high proportion of optimal commute trips within a zone, e.g., 90.7 percent in Small and Song (1992) were intrazonal commute. If one adopts average reported intrazonal commuting time for all zones in a study area, the optimal commute is likely to be overestimated. An inflated optimal commute leads to an underestimated wasteful commuting such as the case for White (1988) that was only 11 percent. Based on a smaller zone, i.e., Traffic Analysis Zones (TAZs), Small and Song (1992) implemented White's LP approach in Los Angeles and found 66 percent wasteful commuting, substantially higher than White's but lower than Hamilton's. Their finding confirmed Hamilton's proposition of scale effect. In addition, they suggested a normatively neutral term excess commuting instead of wasteful commuting. Horner and Murray (2002) linked the issue to the Modifiable Areal Unit Problem (MAUP), which is well known to geographers (Openshaw and Taylor, 1979). They further validated the impact of spatial unit definition on the estimation of wasteful commuting and suggested using zonal data as disaggregate as possible.

Others suspected that different metrics might play a role (Hamilton, 1989). Hamilton (1982) used distance while White (1988) used travel time. Most found a high consistency between the

two and rejected that it was a major factor causing the discrepancy (e.g., Cropper and Gordon, 1991; Small and Song, 1992).

Some believed that job decentralization might account for most or all of the wasteful commuting (Merriman et al., 1995; Suh, 1990). However, as argued by Giuliano and Small (1993), the direction of job decentralization's impact on commuting could be ambiguous. On the one side, it may encourage urban sprawl, reduce the land use intensity and thus increase commute lengths. On the other side, it may also improve the jobs-housing balance in many areas particularly suburbia and alleviate the need of lengthy commute to downtown. Following the suggestions of Hamilton (1982), several studies searched for factors beyond land use that prevented people from attaining optimal commute. Some emphasized the variability of labor participation rate across households as it is harder for households with multiple workers to optimize commuting for individuals (Kim, 1995; Thurston and Yezer, 1991). Certainly, residential choice is hardly made solely for the purpose of minimal commuting and often involves a complex decision considering also housing and neighborhood attributes (Cropper and Gordon, 1991). Not all workers are mobile in terms of residential choice and thus limit their likelihood of relocating to save commute (Buliung and Kanaroglou, 2002). Furthermore, the boundary effect for a study area may also affect the magnitude of wasteful commuting as Frost et al. (1998) found in their study of British cities. Our fascination of wasteful commuting is also linked to its implication in public policy (Fan et al., 2011). Many studied the issue for various transportation or land use related policy scenarios that could reduce commuting cost and their related environmental and economic impacts (Boussauw et al., 2012; Horner, 2002; Ma and Banister, 2006; O'Kelly and Lee, 2005; Rodríguez, 2004; Scott et al., 1997; Yang, 2008).

This research directs the attention back to the measurement of wasteful commuting given a

land use pattern (i.e., employment and resident worker locations). Is it possible to design a study as disaggregate as possible to mitigate (or perhaps be even free from) the scale effect for estimating required commute, as suggested by Horner and Murray (2002)? Given the concern related to privacy, it is unlikely for researchers to access a large scale commuting dataset of individual households geocoded to their home addresses and workplaces. Our approach is to simulate individual employment and resident worker locations and the trips between them in order to alleviate the concern of unreliable estimate of intrazonal commute and also improve the accuracy of estimating interzonal commute lengths.

Another issue is on how actual commute is measured. Some commuting literature (though not directly related to wasteful commuting) suggested the unreliability of measuring commute length by travel time. It could be misleading as travel time by slower modes (e.g., carpool, transit, walking or bicycling) is much longer than drove-alone for the same distance. The journey-to-work survey (e.g., CTPP) data often contain some erroneous records (e.g., commute trips of several hours for travelling only a few miles; for example, the reported mean travel time from tract 36.04 to tract 11.04 in Baton Rouge, Louisiana was 3.7 hours (with an estimated travel distance 5.4 miles), 2.8 hours from tract 22 to 26.01 (with an estimated travel distance 2.6 miles), and so on). There is also concern of inconsistency in the way respondents report commute time (e.g., whether including “mental time” as noted in Wang (2003)). Wasteful commuting calculated at different times may also vary (Frost et al., 1998; Yang, 2008). As wasteful commuting is the difference between actual and optimal commuting, it is an unfair comparison to define actual commuting by reported time and optimal commuting by estimation. This research proposes to measure both by estimated travel time and distance through the road network, and identify the true extent of wasteful commuting.

### **CHAPTER 3. STUDY AREA AND DATA SOURCES**

As the core of Baton Rouge Metropolitan Area, East Baton Rouge Parish in Louisiana is selected as the study area. Note that parish in Louisiana corresponds to county in other states in the United States. This parish has an area of 471 square miles including the City of Baton Rouge (i.e., the state capital, one of the fastest growing areas in the South) in the middle, Baker and Zachary in the north. Eight parishes surround it, and the spatial distribution of this region is shown in Figure 1. There are two major rivers in this region—Mississippi River and Amite River—forming the natural borders of the study area. Clearly, the Mississippi River on the west divides East Baton Rouge Parish from West Baton Rouge Parish and Pointe Coupee Parish, while the Amite River on the east segregates this Parish from Livingston Parish and St. Helena Parish. In terms of land use, these neighbor parishes are mostly composed of rural areas (Antipova et al., 2011). Based on the road density in Figure 1, the northeastern, northwestern and the most southern parts of East Baton Rouge Parish are also recognized as rural areas that may serve as the buffer zone between the urbanized areas (e.g., most central area that has high road density) in this parish and other neighboring parishes. Given the above distribution patterns, edge effects, a common phenomenon that could result in unreliable conclusions due to incomplete consideration of the impacts of border areas, might be of little influence in this study area (Wang et al., 2011). For simplicity, hereafter the study area is referred to as Baton Rouge.

The major data source is the CTPP: the 1990 and 2000 CTPPs from the Bureau of Transportation Statistics (BTS, 2014), and the most recent 2006-2010 CTPP from the American Association of State Highway and Transportation Officials (AASHTO, 2014). Note that the 1990 or 2000 CTPP was extracted from the long form decennial census, and the 2006-2010 CTPP was based on the 5-year American Community Survey (ACS) 2006-2010 (hereafter simply referred to

as 2010). All CTPPs consist of three parts: (1) part 1 on place of residence, such as number of resident workers and breakdowns of wage groups, and mean wage rate in each zone; (2) part 2 on place of work (this is unique among all census products), such as number of jobs and breakdowns of wage groups in each zone; and (3) part 3 on journey-to-work flow, such as number of commuters from a residence zone to a workplace zone, and mean commuting time breakdowns of different transportation modes, for example, drove-alone, carpool, public transit, and walk.

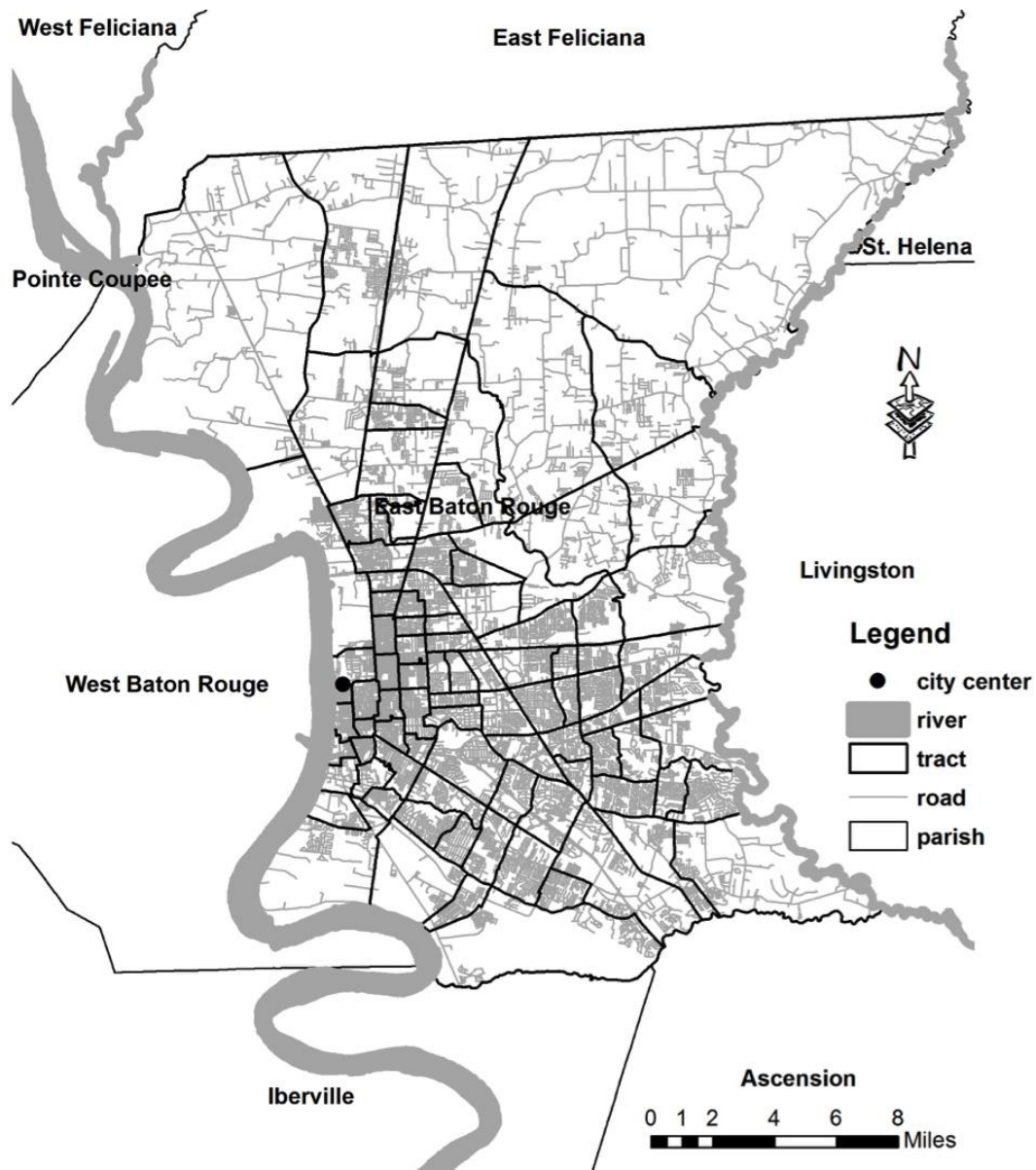


Figure 1. Baton Rouge region 2010.

There is inconsistency in area unit used in the CTPP data for Baton Rouge: traffic analysis zone (TAZ) in 1990, multiple zonal levels in 2000 (census tract, census block group, and TAZ for Parts 1 and 2, only census tract for Part 3), and census tract and TAZ in 2006-2010. We chose census tracts as the unit to use throughout. Luckily in Baton Rouge, the 1990 TAZs were mostly components of census tract for easy aggregation with only very few minor exceptions. There were 85, 89 and 92 census tracts in Baton Rouge in 1990, 2000 and 2010, respectively (excluding the 2010 airport tract where no records of any resident workers or jobs are provided in the data). The slightly increased number of tracts in later years were simply the result of split tracts from earlier years (i.e., 2000 vs. 1990, 2010 vs. 2000). This enabled us to integrate the data in three time epochs based on the 85 census tracts in 1990 when needed. Corresponding spatial data sets in GIS (including census tracts, TAZs and road networks) are extracted from the TIGER Products 1994, 2000, and 2010 from the U.S. Census Bureau. We are aware of the time gaps of using the 1994 and 2010 GIS data to match the 1990 and 2006-2010 CTPP, respectively, which were the best data accessible to us.

The National Land Cover Database (NLCD, <http://www.mrlc.gov>), a national land cover product created by the Multi-Resolution Land Characteristics (MRLC) Consortium, is used to help improve the accuracy of individual trip simulation, in particular the simulation of trip destinations (see Chapter 4). Three NLCD products—e.g., NLCD 1992, 2001, and 2011—are employed to match with the above CTPP and TIGER data. The NLCD has a spatial resolution of 30 square meters, and only one land cover type is recorded in each pixel, 30m × 30m polygon. It provides a uniform land cover classification across the entire United States, and is perhaps the most accessible and commonly used national land cover map (Jin et al., 2013). In this research, the high intensity developed areas that are commonly interpreted as commercial/industrial lands are used to define

the geographic areas for simulated job locations. The geographic areas of resident workers, however, are calibrated on the basis of census block population data obtained from the U.S. Census Bureau due to its better accuracy in capturing the residential pattern than the NLCD. See Table 1 for a summary of all data sources used in this research.

Table 1. Summary of all data sources.

<b>Data layer</b>	<b>Year</b>	<b>Spatial scale</b>	<b>Format</b>	<b>Source</b>	<b>Purpose</b>
CTPP	1990	TAZ	ASCII/excel file	BTS	Total number of workers, jobs, and commuters
	2000	Census tract	ASCII/excel file	BTS	
	2010 <sup>1</sup>	Census tract	ASCII/excel file	AASHTO	
Zone boundary	1994	TAZ	Vector/shapefile	TIGER/Line	Define boundary of zone units
	2000	Census tract	Vector/shapefile	TIGER/Line	
	2010	Census tract	Vector/shapefile	TIGER/Line	
Population	1990	Census block	ASCII/excel file	Census	Spatial extent of residential areas
	2000	Census block	ASCII/excel file	Census	
	2010	Census block	ASCII/excel file	Census	
NLCD	1992	30m×30m cell	Raster/tif file	MRLC	Spatial extent of workplaces
	2001	30m×30m cell	Raster/tif file	MRLC	
	2011	30m×30m cell	Raster/tif file	MRLC	
Road network	1994	-	Vector/shapefile	TIGER/Line	Define entire road network
	2000	-	Vector/shapefile	TIGER/Line	
	2010	-	Vector/shapefile	TIGER/Line	

<sup>1</sup> Based on 2006-2010 CTPP, 2010 is used here and all other tables for simplicity.

## **CHAPTER 4. MONTE CARLO SIMULATION METHOD**

This research proposes to use Monte Carlo simulation technique to simulate individual locations of home and job sites as well as the trips between them. By mitigating the aggregation error and zonal effect, this permits more accurate estimation of commute distances in both analyses of commuting pattern and commuting efficiency (i.e., wasteful commuting) in this research. This chapter will provide a brief introduction to the Monte Carlo simulation technique and a specific application of simulating locations of trip ends (i.e., resident workers and jobs) and trip distribution (i.e., trips between resident workers and jobs).

### 4.1 INTRODUCTION TO MONTE CARLO SIMULATION

Basically, a Monte Carlo method generates suitable random numbers of parameters or inputs to explore the behavior of a complex system or process. The random numbers generated follow a certain probability distribution function (PDF) that describes the occurrence probability of an event. Some common PDFs include:

- A normal distribution is defined by a mean and a standard deviation. Values in the middle near the mean are most likely to occur, and the probability declines symmetrically from the mean.
- If the logarithm of a random variable is normally distributed, the variable's distribution is lognormal. For a lognormal distribution, the variable takes only positive real values, and may be considered as the multiplicative product of several independent random variables that are positive. The left tail of a lognormal distribution is short and steeper and approaches toward 0, and its right tail is long and flatter and approaches toward infinity.



- In a uniform distribution, all values have an equal chance of occurring.
- A discrete distribution is composed of specific values, each of which occurs with a corresponding likelihood. For example, there are several turning choices at an intersection, and a field survey suggests a distribution of 20 percent turning left, 30 percent turning right and 50 percent going straight.

In a Monte Carlo simulation, a set of random values is generated according to a defined probability distribution function (PDF). Each set of samples is called an iteration and recorded. This process is repeated a large number of times. The larger the number of iteration times is simulated, and the better the simulated samples conform to the pre-defined PDF. Therefore, power of a Monte Carlo method relies on a large number of simulations. By doing so, Monte Carlo simulation provides a comprehensive view of what may happen and the probability associated with each scenario.

Monte Carlo simulation is a means of statistical evaluation of mathematical functions using random samples. Software such as Matlab and R package provides several random number generators corresponding to different PDFs (e.g., a normal distribution). Others use pseudo-random number sampling. For example, the inverse transformation generates sample numbers at random from a probability distribution defined by its cumulative distribution function (CDF), and is therefore also called inverse CDF transformation. Specifically, one can generate a continuous random variable  $X$  by (1) generating a uniform random variable  $U$  within  $(0, 1)$ , and (2) setting  $X = F^{-1}(U)$  for transformation to solve  $X$  in terms of  $U$ . Similarly, random numbers following any other probability distributions could be obtained.

#### 4.2 MONTE CARLO SIMULATIONS OF RESIDENT WORKERS (O) AND JOBS (D)

This section and next one introduce a specific application of Monte Carlo simulation in data disaggregation, one from area-based aggregated data to individual points (e.g., from area-based job count data to individual job points) and another from area-based flow data to individual O-D trips (e.g., from area-based commuting flow count data to individual journey-to-work trips). Both are commonly encountered in spatial analysis.

To mitigate the effect of aggregation error and zonal scale commonly seen in commuting studies, we begin with simulating locations of trip ends, i.e., a simulation of individual locations of resident workers and jobs that are proportional to their corresponding numbers within each census tract (i.e., following a discrete distribution). Land use patterns are considered for better simulation performance. Specifically, the number of simulated trip origins is proportional to the number of resident workers in a tract, the number of trip destinations is proportional to the number of jobs there, and both are randomly distributed within areas of residential land use (from census block data) and areas of commercial/industrial land use (from the NLCD) in the tract's boundary, respectively (see Figure 2 for the distribution of commercial/industrial land use patterns in Baton Rouge derived from NLCD 2011). In other words, denoting the total numbers of simulated and actual commuters by  $n$  and  $N$ , respectively, and given the numbers of resident workers and employment in a tract  $i$  from the CTPP as  $R_i$  and  $E_i$ , the numbers of simulated individual workers and jobs in the tract  $i$  are  $(n/N)R_i$  and  $(n/N)E_i$ , respectively. The value of  $n$  is selected by balancing accuracy and computational efficiency (i.e., larger numbers of simulated points and subsequently O-D trips improve accuracy but demand more computing power). For illustration of the process, we selected four census tracts in

Baton Rouge as an example. Given the zonal level spatial patterns of resident workers and jobs confined with corresponding land uses in the four selected tracts in Figure 3a and Figure 3c, respectively (see Figure 4a and Figure 4c for the case without considering land use patterns), Figure 3b and Figure 3d show corresponding simulated individual locations of resident workers and jobs, more reasonable and accurate results compared to Figure 4b and Figure 4d that do not take land use patterns into account.

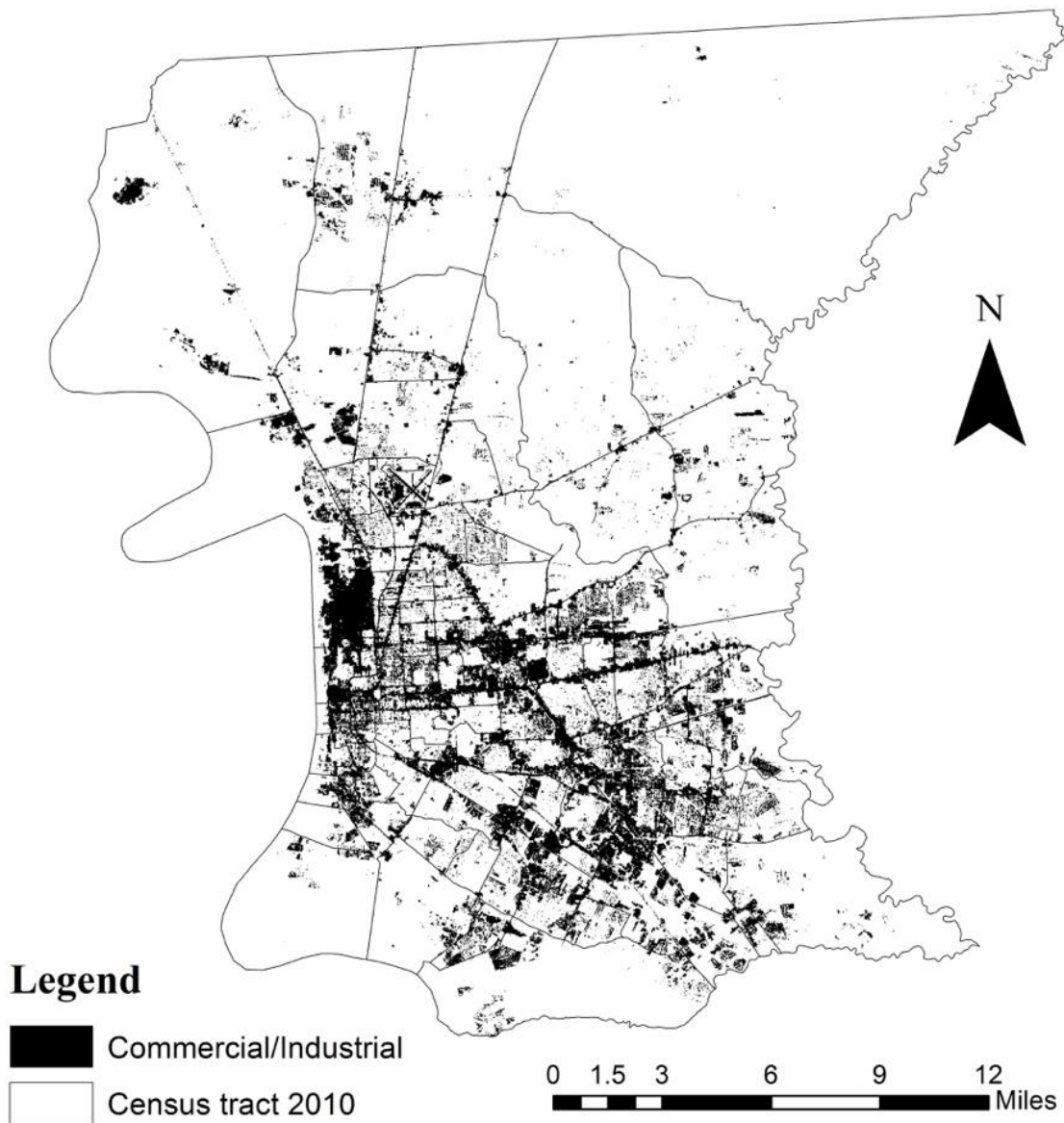
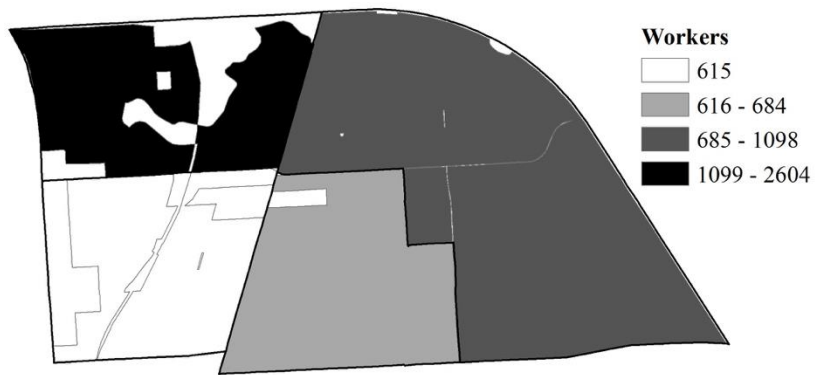


Figure 2. Commercial/Industrial land use in Baton Rouge 2010.



(a)



(b)



(c)



(d)

Figure 3. Spatial distribution of (a) resident workers in residential land use areas in zones, (b) simulated resident workers, (c) jobs in commercial/industrial land use areas in zones, and (d) simulated jobs.

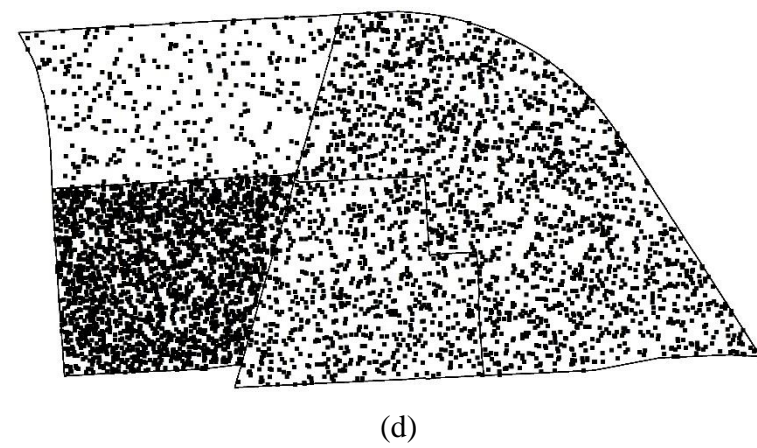
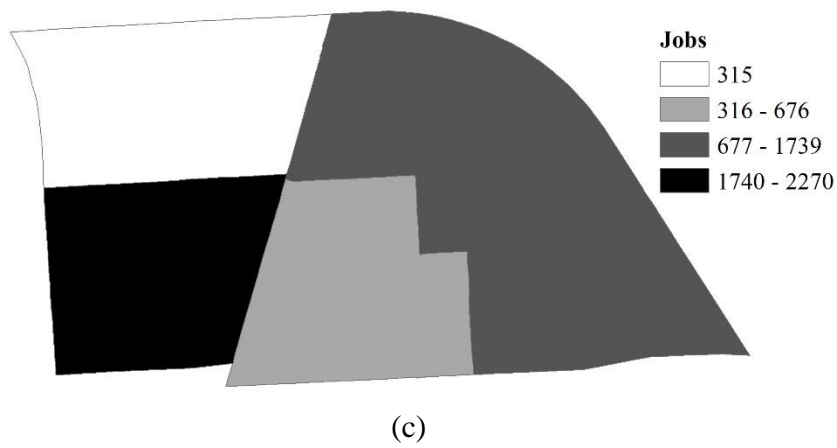
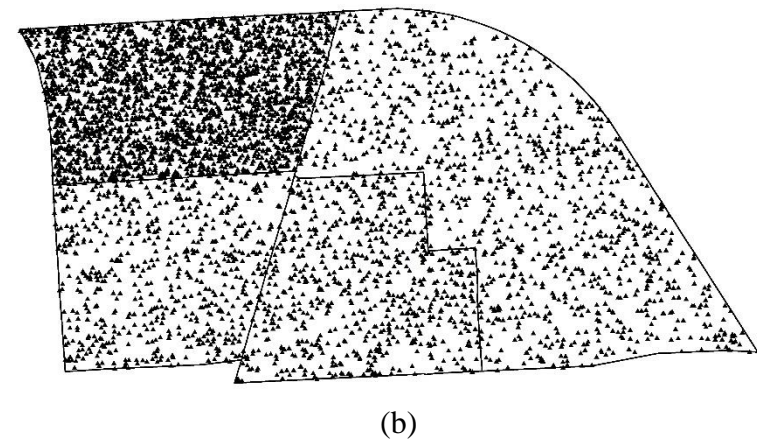
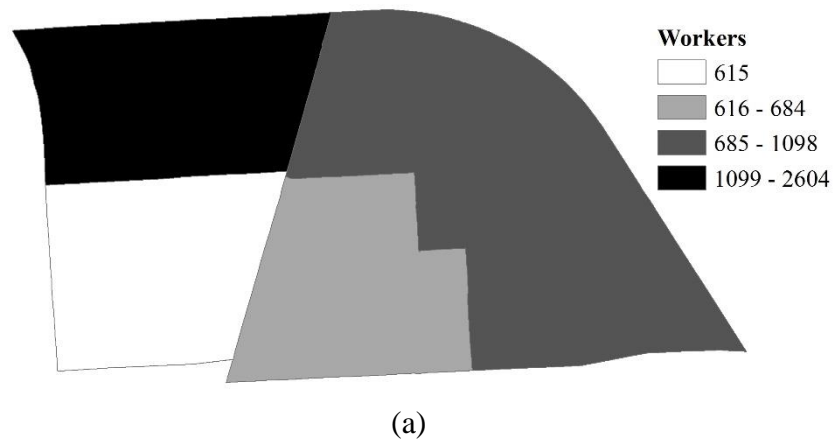


Figure 4. Spatial distribution of (a) resident workers in zones, (b) simulated resident workers, (c) jobs in zones, and (d) simulated jobs.

### 4.3 MONTE CARLO SIMULATIONS OF O-D TRIPS

The previous section returns simulated points of resident workers and jobs according to their spatial distributions across the areal unit (e.g., census tract). This section shows another application of Monte Carlo simulation in connecting resident workers and jobs together to form commuting trips, or more generally, disaggregating area-based flow data to individual O-D trips.

To achieve this, another simulation process is designed for trip distribution. Specifically, we simulate the trips between individual locations of workers and jobs that are consistent with the actual zonal-level flows. Similarly, as the actual zonal-level flow from a residential worker tract  $i$  to an employment tract  $j$  (extracted from the CTPP) is  $x_{ij}$ , the simulated flow when aggregated at the zonal level should be  $(n/N)x_{ij}$ , i.e., proportional to the actual journey-to-work pattern. This is implemented by another Monte Carlo simulation process by utilizing the previously simulated points of resident workers (O) and jobs (D):

- Randomly choosing an origin point  $p(i)$  in a residential worker tract  $i$ ,
- Randomly choosing a destination point  $q(j)$  in a job tract  $j$ ,
- Forming individual O-D trips between  $p$  and  $q$  and recording the trip length between them through the road network  $c_{pq}$ , and
- Capping the number of trips between zones  $i$  and  $j$  at  $(n/N)x_{ij}$ .

The simulation approach disaggregates the reported zonal commuting trips into individual trips, and permits more accurate estimation of commute distances by mitigating the aggregation error and zonal effect. For example, the mean within-tract commute distance for the most northeast tract in 2010 in Figure 1 was 0 by the centroid-to-centroid measure, and became 8.39 miles by the simulation approach, and 7.74 miles after land use variability was accounted for.

## **CHAPTER 5. COMMUTING AND LAND USE**

This chapter examines the temporal trend of commuting for the general population (resident workers), and then attempts to understand the observed commuting pattern. As mentioned, commuting may be explained by where they are (i.e., spatial factors) and who they are (i.e., nonspatial factors) (Wang 2003). One spatial factor that is commonly investigated in existing studies (i.e., land use) is tested in this chapter; and the effect of a nonspatial factor on commuting is examined in next chapter.

### 5.1 OVERALL TEMPORAL TREND OF COMMUTING

This research examines the commuting pattern in both distance and time. Unlike commuting time, distance is not reported in CTPP. Given the aforementioned issues, we retrieve commuting distance based on simulation of individual trips for better accuracy.

People commute by multiple modes. It makes more sense to take mode choices into consideration when measuring commuting distance. For example, Wang (2000) recovered commute distance based on the centroid-to-centroid network distance in Chicago by two major modes—vehicles (including drove-alone, carpool, bus, taxi, etc.) and trains (subway and rail) due to the high percentage in each mode. Specifically, he calculated the shortest-time network distance for commuting trips made by vehicles and train, while using the Manhattan distance to estimate the commute distances for commuters using bicycle or walking. Separation by different transportation modes is truly reasonable, especially for area with high demand in each mode, and additional information such as the transit network would be needed. In Baton Rouge, however, the majority commuted by auto (including drove-alone and carpool), and the percentage was steady over time (i.e., 94-95 percent) (see Table 2). Therefore, we estimated commute distance based on the road network without taking transit, bicycle or pedestrian routes into consideration.

Table 2. Modal splits and commute lengths in Baton Rouge 1990-2010.

Year	Modal splits				Mean commute distance	Mean commute time
	Drove-alone	Carpool	Public transit	Others <sup>1</sup>	(mile)	(min)
1990	82.35	11.76	1.29	4.60	5.95	16.73
2000	83.16	11.91	1.40	3.54	6.17	18.73
2010	83.77	11.08	1.75	3.40	6.25	17.98

<sup>1</sup> Others include taxi, motorcycle, bicycle, walk, etc.

The mean commuting distance/time of a zone is commonly seen in the literature as a measure of commuting pattern (Gera, 1979; Gera and Kuhn, 1980; Gordon et al., 1989b; Gordon et al., 1991; Giuliano and Small, 1993; Cervero and Wu, 1998; Wang, 2000; Wang, 2001; Wang, 2003; Kim, 2008; Sultana and Weber, 2014). Similar to Wang (2000, 2001, 2003), mean commuting distance/time in a tract is the average travel distance/time from this tract to all employment tracts weighted by corresponding number of commuters.

$$MC_i = \sum_{j=1}^n \frac{f_{ij}}{R_i} c_{ij} \quad (1)$$

In Equation (1),  $MC_i$  is the mean commute distance/time in tract  $i$ ;  $f_{ij}$  is the commuter flow residing in tract  $i$  and working in tract  $j$ ;  $c_{ij}$  is travel cost (i.e., distance/time) between tract  $i$  and  $j$ ;  $R_i$  is the number of resident workers in tract  $i$ ; and  $n$  is the total number of tracts in the study area. In a word, this measure indicates that resident workers in tract  $i$ , on average, commute as far/long as  $MC_i$ . CTPP part 3 provides the commuter flow matrix and corresponding reported travel time between tracts, which makes it feasible to measure mean commute time for each tract. Mean commute distance, while not reported, was measured based on the Monte Carlo simulation of individual trips, rather than the coarse centroid-to-centroid distance measure. For example, the



average commute distance in Baton Rouge in 2000 was 5.95 miles by the zonal centroid-to-centroid approach, and revised to 6.17 miles by the simulation-based approach. The more accurate (longer) estimates by the simulation technique are validated through a one-tailed statistical test, indicating the effectiveness of our method.

Also shown in Table 2, the mean commute distance on average increased steadily from 5.95 mile in 1990 to 6.17 mile in 2000 and further to 6.25 mile in 2010. This is consistent with some previous studies (Levinson and Kumar, 1994; Cervero and Wu, 1998), and reflects a long standing trend of more workers moving farther from their jobs either to search farther for jobs for maximizing their earnings or to move their residences for better housing. However, the increasing rate was higher in 1990-2000 than in 2000-2010. One possible reason might be the recession in 2008 (Horner and Schleith, 2012).

The mean commute time for overall population increased from 1990 to 2000 and then declined to 2010. Other studies also found that the average commute time stayed stable or even dropped over time, albeit the worsening traffic congestion (Gordon et al., 1989c; Dubin, 1991; Gordon et al., 1991; Levinson and Kumar, 1994; Kim, 2008). They ascribed the declining time to co-location of jobs and housing, i.e., people relocate their residence or jobs to cut back commute time as traffic becomes more congested. An increasing use of suburban roads that are usually newer and wider than roads in central city makes it achievable to commute longer distance in a shorter duration. Taking drove-alone for example, the implied average commuting speed was 24.3 mph in 1990, dropped to 21.9 in 2000 and only recovered slightly to 22.8. Therefore, a small increment in commute distance from 1990 to 2000 came with a much larger climb in commute time, and it was only after 2000 that the co-location theory became relevant and led to a small drop in commute time. The significant climb of commute time for 1990-2000 might reflect people's increasing

endurance of long commutes or traffic congestion that grew much more rapidly than people could adapt (Levinson and Wu, 2005), and the re-location adjustment came afterwards. Such an increase of commuting time in 1990-2000 was also seen in Pisarski (2002).

Based upon the observed commuting pattern (both distance and time) as listed in Table 2, we may ask questions on why and how. In short, we need to find the underlying factors that significantly affect commuting. This chapter focuses on the spatial part (i.e., land use, the spatial distributions of employment and resident workers). As mentioned in Chapter 2, existing attempts look at three aspects of land use patterns (i.e., distance from CBD, a local jobs-housing balance ratio, and the overall proximity to jobs) and link them with commuting. Specifically, distance from CBD captures how far a residential location is from a job concentration area (particularly applied to a monocentric city where its CBD dominates the job market); the local jobs-housing balance ratio further extends the measure by considering local jobs (within a threshold of residence) rather than jobs in one particular area (e.g., CBD); and the job proximity, collectively, measures the distance from a residential location to the overall job market. Next, I will evaluate the effects of these land use metrics on commuting one by one.

## 5.2 COMMUTING PATTERN VS. DISTANCE FROM CBD

There has been a long tradition of attempts to explain intraurban variability of commuting by land use patterns. The analysis begins by examining the impact of the CBD with the highest employment concentration (see Figure 5). In the study area, 42 percent of workers commuted to the area within a 3-mile radius of the CBD in 1990, and the rate dropped to 32 percent in 2000 and 31 percent in 2010, indicating that a large portion of jobs were concentrated in CBD area albeit they increasingly moved out of the CBD area during this period. Table 3 shows that distance from the CBD (denoted by  $D_{\text{CBD}}$ ) explained the variation of mean commute distance across census tracts

by 78 percent in 1990, 68 percent in 2000 and 63 percent in 2010. The declining explaining power was attributable to dispersion of jobs beyond the CBD area (e.g., percentage of workers commuted to the area within a 3-mile radius of the CBD was 42 percent in 1990, 32 percent in 2000 and 31 percent in 2010). The effect of distance from CBD remained significant on mean commute time in all models (Table 4), but much weaker than on mean commute distance (Table 3). The lower performance of regression models on commute time was attributable to the non-uniform modal distribution across tracts. In fact, for drove-alone commuters alone, the pattern of mean commute time was largely consistent with that of mean commute distance, and the corresponding regression models yielded  $R^2 = 0.60, 0.41$  and  $0.50$  in 1990, 2000 and 2010, respectively (details not reported here). Adding the square term  $D_{CBD}^2$  did not improve the explaining power of the regression models and thus was not included. Note that results on jobs-to-workers-ratio (JWR) and proximity to jobs (JobP) are also reported in Table 3 and Table 4, see the following sections for details.

Table 3. Regression models of mean commute distance across census tracts 1990-2010.

	1990	2000	2010	1990	2000	2010	1990	2000	2010
Intercept	2.40*** (10.03)	2.91*** (10.52)	3.01*** (9.93)	10.37*** (29.14)	14.87*** (20.75)	13.65*** (21.34)	0.88*** (4.60)	0.99*** (7.06)	1.10*** (5.74)
$D_{CBD}$	0.57*** (17.38)	0.50*** (13.67)	0.48*** (12.22)						
JWR				-3.88*** (-14.07)	-10.38*** (-8.35)	-8.05*** (-7.57)			
$JWR^2$				0.37*** (13.93)	2.60*** (5.33)	1.75*** (4.36)			
JobP							0.67*** (29.44)	0.67*** (40.26)	0.64*** (29.22)
No. obs.	85	89	91	85	89	91	85	89	91
$R^2$	0.78	0.68	0.63	0.72	0.78	0.76	0.91	0.95	0.91

Note: t-statistics are in parentheses; \*\*\* significant at the 0.001 level.

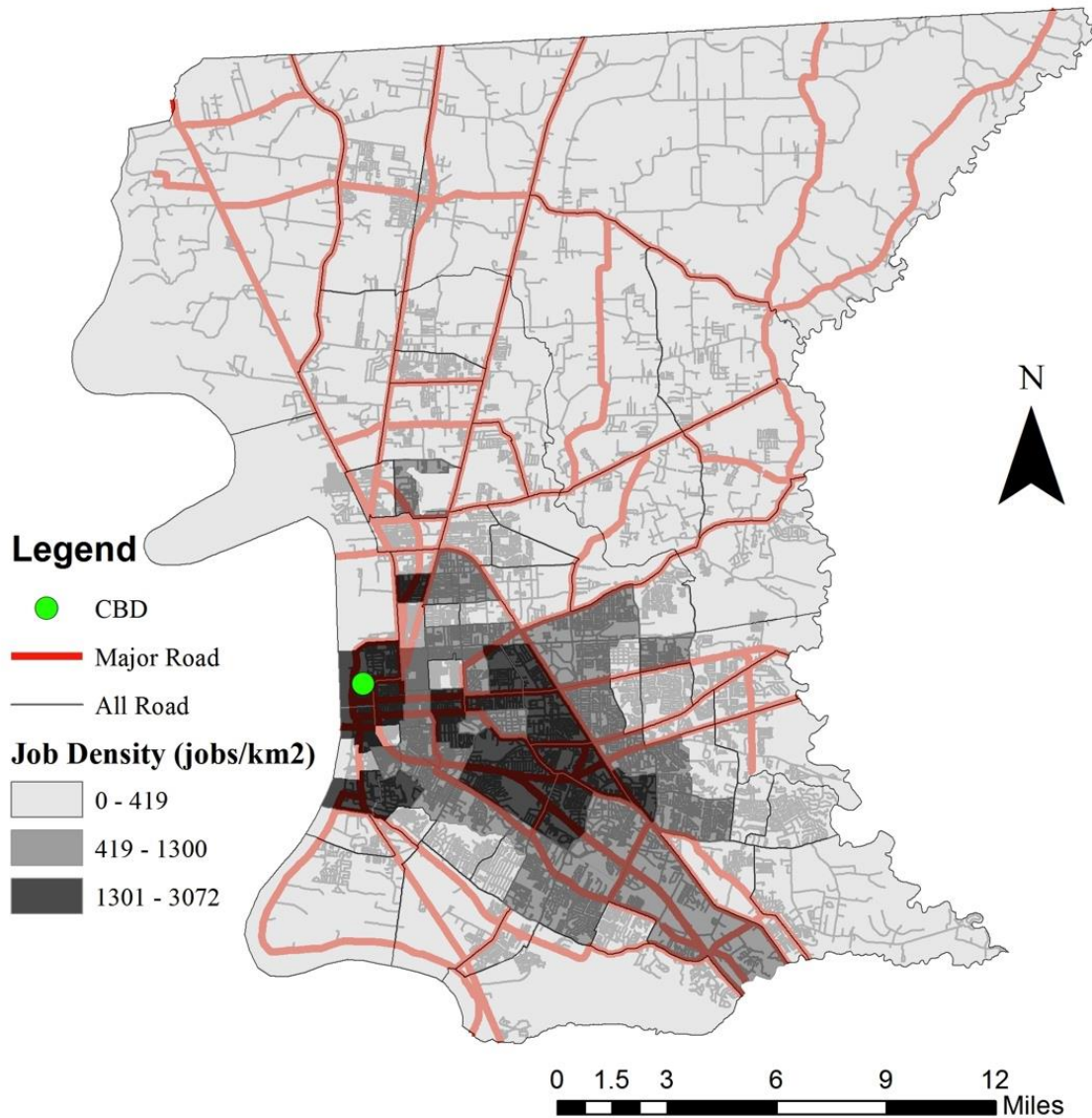


Figure 5. Job density pattern in Baton Rouge 2010.

### 5.3 COMMUTING PATTERN VS. JOBS-HOUSING BALANCE

This section looks into the jobs-housing balance hypothesis proposed by Cervero (1989). An imbalanced area has far more resident workers than jobs, and thus more workers need to commute outside of the area for their jobs and tend to incur more commuting. Following Wang (2000), this research used the floating catchment area method to define a circular area around each census tract centroid, and calculated the jobs-to-workers-ratio (JWR) within each catchment area. A higher

JWR implies less need of commuting beyond the catchment area and thus is expected to correlate with less commute. We experimented with radii ranging 1.5-7.5 miles and settled with 5 miles for its best explaining power.

As an example, Figure 6 shows the relationship between mean commute distance and time versus JWR in 2010. Both display a quadratic trend, but the trend is much clearer for distance than time. This is confirmed by a regression model with the added square term of JWR, as reported in Tables 2 and 3. In 1990, 2000 and 2010, the negative sign of JWR and the positive sign of  $JWR^2$  indicate that mean commute distance or time at the tract level declined with JWR, but the declining slope got flatter in higher-JWR areas. Both terms are statistically significant in all models. The models for mean commute distance in Table 2 performed well with  $R^2$  that was 0.72 in 1990, peaked at 0.78 in 2000 and dropped slightly to 0.76 in 2010. The models for mean commute time in Table 3 also confirmed the quadratic trend in all years though with lower  $R^2$  (0.21, 0.26 and 0.35 in 1990, 2000 and 2010, respectively). In short, the results confirm the importance of jobs-housing imbalance in affecting commuting pattern, much more significant in Baton Rouge than large metropolitan areas reported in other studies (e.g., Wang, 2000).

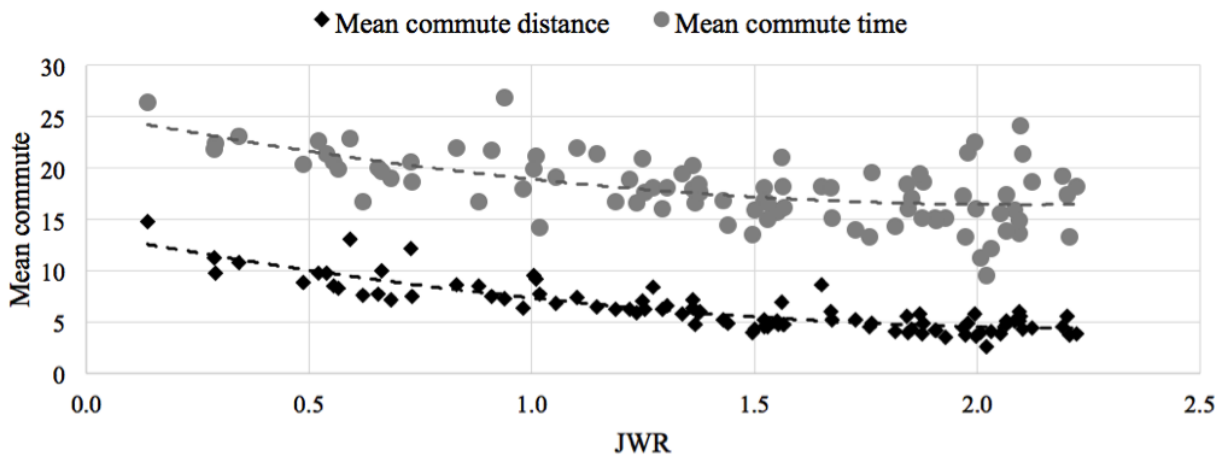


Figure 6. Mean commute distance and time vs. jobs-to-workers ratio (JWR) in 2010.

Table 4. Regression models of mean commute time across census tracts 1990-2010.

	1990	2000	2010	1990	2000	2010	1990	2000	2010
Intercept	14.72*** (26.82)	16.96*** (23.06)	15.29*** (25.01)	19.69*** (28.25)	27.86*** (13.51)	25.36*** (17.12)	13.32*** (20.44)	14.42*** (16.12)	13.63*** (21.15)
D <sub>CBD</sub>	0.32*** (4.28)	0.27** (2.80)	0.40*** (5.04)						
JWR				-2.51*** (-4.65)	-12.26*** (-3.43)	-8.45*** (-3.43)			
JWR <sup>2</sup>				0.21*** (4.12)	3.60* (2.57)	1.99* (2.15)			
JobP							0.25*** (5.74)	0.30*** (5.22)	0.31*** (7.41)
No. obs.	85	89	91	85	89	91	85	89	91
R <sup>2</sup>	0.18	0.08	0.22	0.21	0.26	0.35	0.28	0.24	0.38

Note: t-statistics are in parentheses; \* significant at the 0.05 level, \*\* significant at the 0.01 level, \*\*\* significant at the 0.001 level.

#### 5.4 COMMUTING PATTERN VS. PROXIMITY TO JOBS

Either the emphasis on the role of CBD or the jobs-housing balance approach does not consider all job locations in explaining the commuting pattern. The job proximity index (JobP) captures the spatial separation between a worker's residence location and all potential job sites (Wang, 2003), formulated such as:

$$JobP_i = \sum_{j=1}^n P_{ij} d_{ij}, \quad (2)$$

$$\text{where } P_{ij} = \left( J_j d_{ij}^{-\beta} \right) / \sum_{k=1}^n \left( J_k d_{ik}^{-\beta} \right).$$

Similar to the notion of Huff (1963) model, the probability of workers residing in zone  $i$  and going to work in zone  $j$  (denoted by  $P_{ij}$ ) is predicted as the gravity kernel of job site  $j$  out of those

of all job sites  $k$  ( $= 1, 2, \dots, n$ ). Each gravity kernel is positively related to the number of jobs there  $J_j$  (or  $J_k$ ) and negatively to the distance or time (measured as network distance or time) between them  $d_{ij}$  (or  $d_{ik}$ ) powered to the distance friction coefficient  $\beta$ . With the probability  $P_{ij}$  defined, JobP at zone  $i$  is simply the aggregation of all distances (time)  $d_{ij}$  with corresponding probabilities  $P_{ij}$  over all job sites ( $j = 1, 2, \dots, n$ ).

Calibration of JobP requires defining the value for the distance friction coefficient  $\beta$  in Equation (3). In this research, the  $\beta$  value was computed from the log-transformed regression based on the classic gravity model such as

$$C_{ij} = aW_iJ_jd_{ij}^{-\beta} \quad (3)$$

where  $C_{ij}$  is the number of commuters from a tract with  $W_i$  resident workers and to a tract with  $J_j$  jobs for a distance (time) of  $d_{ij}$  (Wang 2015, p.33). Based on the CTPP data, the derived  $\beta$  value was 0.404 in 1990, 0.547 in 2000, and 0.475 in 2010 if the journey-to-work trips were measured in distance; and the  $\beta$  value was 0.295 for 1990, 0.353 for 2000, and 0.385 for 2010 if measured in time.

The regression results for mean commute distance and time by JobP are again reported in Table 3 and Table 4, respectively. The mean commute distance at the tract level was well explained by JobP with  $R^2 = 0.91, 0.95$  and  $0.91$  in 1990, 2000 and 2010, respectively. This is a significant improvement over other factors, i.e.,  $D_{CBD}$  and  $JWR$ . Similarly, regression models on mean commute time returned lower  $R^2$  ranging 0.24-0.38. We also did not add the square term  $JobP^2$  as it did not improve the explaining power of the regression models. Note that we also run a series of regression models on mean commuting distance (centroid-to-centroid), and results indicate weaker  $R^2$  than the simulation-calibrated distance. This again demonstrates the value of our simulation approach.

## **CHAPTER 6. COMMUTING AND WAGE RATE**

Alternatively, this chapter makes an attempt to understand intraurban commuting based upon nonspatial factors. As mentioned in Chapter 2, commuters of different socioeconomic groups like age, gender, income, race and among others usually have varying commuting preferences and patterns. Studies of this kind commonly rely on aggregated socioeconomic data such as from Census; and this would make such analyses most vulnerable and open to criticism due to the ecological nature, however. Therefore, this research focuses on only one specific nonspatial factor to examine the connection between commuting pattern and aspatial factors, instead of investigating all of those aforementioned nonspatial factors.

This research finally selected the nonspatial factor income and aims at understanding its relationship with the observed commuting pattern (i.e., commuting variability by different income groups). Specifically, we use wage rate earned by resident workers instead of household income because of better data on wages from the CTPP and for wage's closer tie to commuting behavior than other income sources (Gera and Kuhn, 1980; Wang, 2003).

There are several reasons for picking income (wage as a surrogate): (1) it plays a determining role in a household's residential choice that is usually driven by the tradeoff between commuting length and housing size as suggested by the urban economic model; for example, some people may be more sensitive to one factor than the other according to their socio-demographic attributes, and perhaps foremost, the elasticity value varies across wage groups; (2) it is perhaps the most important determinant in vehicle ownership and thus affects mobility (commuting); (3) it is freely available from CTPP at the neighborhood (e.g., census tract) level, which reflects the neighborhood attributes and provides the geographic context for this research.



## 6.1 COMMUTING PATTERN BY NEIGHBORHOOD'S AVERAGE WAGE

As stated previously, people of different wage rates may have varying responses to the tradeoff between commute length and house size. Without access to data of individual commuters, this section investigates the effect of wage on commuting by using a neighborhood's mean wage rate extracted from the CTPP Part 1.

Table 5. Mean commute distance and time by tract-level mean wage rate.

Mean Wage Percentile	Wage cutoff point			Mean commute distance (mile)			Mean commute time (min)		
	1990	2000	2010	1990	2000	2010	1990	2000	2010
0-20	14,822	21,085	27,529	4.58	5.10	5.40	16.78	20.39	17.51
20-40	18,420	24,140	34,905	4.68	5.67	6.33	16.50	19.40	19.32
40-60	22,766	31,915	45,023	7.95	7.53	5.96	18.66	19.38	17.52
60-80	28,050	41,680	53,551	6.72	7.28	7.14	16.57	18.83	18.10
80-100	42,760	63,245	75,899	5.84	5.21	6.43	15.13	15.49	17.50
Total	-	-	-	5.95	6.17	6.25	16.73	18.73	17.98

To account for the effect of wage inflation over time, we group the tracts in each year by their mean wage rate percentiles such as 20, 40, and so on, as shown in Table 5. In 1990 and 2000, the tract-level mean commuting distance increased with the mean wage rate up to about the middle point (i.e., 40-60 percentile) and then declined toward the wealthiest neighborhood. This is largely consistent with the finding of Cleveland in 1990 reported in Wang (2003). The average commute distance peaked at the middle-range wage neighborhoods in our study area but more to the side of upper-middle wage neighborhoods in Cleveland. In other words, the response of mean commute distance to rising mean wage in neighborhoods may be characterized by a convex shape in 1990 and 2000. This is further confirmed by the convex curves in Figure 7 (for 1990 as an example) and the regression

results in Table 6 (note the + and - signs for the coefficients of mean wage and its square terms, respectively, in 1990 and 2000, and both are statistically significant in either year). However, this pattern was less clear and not significant in 2010 because the middle 40-60-percentile tracts experienced a minor dip in commute distance; and in general, higher wage groups travelled farther than lower wage groups (e.g., 7.14 and 6.43 miles by the 60-80 and 80-100-percentile groups, respectively, vs. 5.40 and 6.33 miles by the 0-20 and 20-40-percentile groups, respectively).

Table 6. Regression of mean commute vs. mean wage rate during 1990-2010.

Dependent variable	Mean commute distance			Mean commute time		
	1990	2000	2010	1990	2000	2010
Intercept	-0.61 (-0.31)	-0.19 (-0.10)	3.12 (1.63)	13.02*** (5.52)	16.97*** (6.02)	13.21*** (4.91)
Mean_wage	0.001** (3.16)	0.0004*** (3.52)	0.0001 (1.30)	0.0004* (2.03)	0.0002 (1.42)	0.0003 (1.91)
Mean_wage <sup>2</sup>	-1.0E-8** (-2.85)	-5.9E-9*** (-3.55)	-1.1E-9 (-0.95)	-1.1E-8* (-2.41)	-5.5E-9* (-2.22)	-3.2E-9 (-1.95)
F value	5.84	6.32	2.58	4.30	11.43	1.91
R <sup>2</sup>	0.13	0.13	0.06	0.10	0.21	0.04
No. observations	85	89	91	85	89	91

Note: *t*-statistics are in parentheses; \*significant at the 0.05 level, \*\*at the 0.01 level, \*\*\*significant at the 0.001 level (two-tailed test).

The convex shape pattern for mean commute distance may first reflect the complex residential choice behavior in the tradeoff between commuting cost and house space. As the income net of commuting cost is larger for higher-wage workers and their housing expenditures increase with income, they opt to live farther away from the central city (and their jobs in general) for more house space and better community environment (Gordon et

al., 1989b; Kim, 2008). In addition, the individual's job location behavior would induce workers to locate their jobs at a distance from their residential places in order to achieve maximization in their earnings net of travel cost and job-searching spending. The job location behavior is more usual in a job-decentralized city (Gera and Kuhn, 1980). The third possible reason refers to the nature of their jobs. Specifically, higher-wage workers usually have jobs requiring more specialties, and thus may need to commute further for appropriate jobs; on the contrary, lower-wage workers usually take less skilled jobs and may find suitable employment everywhere (Prashker et al., 2008). All explanations rely on better transport mobility for workers in higher-wage neighborhoods. Mobility for the workers in lower-wage neighborhoods is more limited (e.g., low vehicle ownership, high dependency on bicycling, walking, or transit that is often feasible only in the central city area). However, this increasing trend of commute distance may be reversed when the mean wage rate reaches a certain level. A higher wage rate also means a higher opportunity cost for more commuting. More importantly, workers living in the neighborhoods of highest wages can also afford homes that are closer to jobs and may command a higher unit price of housing. In short, the high wage enables the workers of this group to cut back on their commute lengths without sacrificing house space.

In terms of mean commute time, the convex shape pattern remained valid in 1990 (i.e., mean commute time peaked at 18.66 minutes in the tracts of the 40-60-percentile wage group), but did not hold in 2000 or 2010. In 2000, clearly the mean commute time was the highest for the poorest tracts and declined steadily to wealthier tracts. In 2010, the highest mean commute time was experienced by the tracts of 20-40-percentile wage group, and varied within a narrow band (i.e., 17.5-18.1 minutes) in the tracts of the other wage groups.

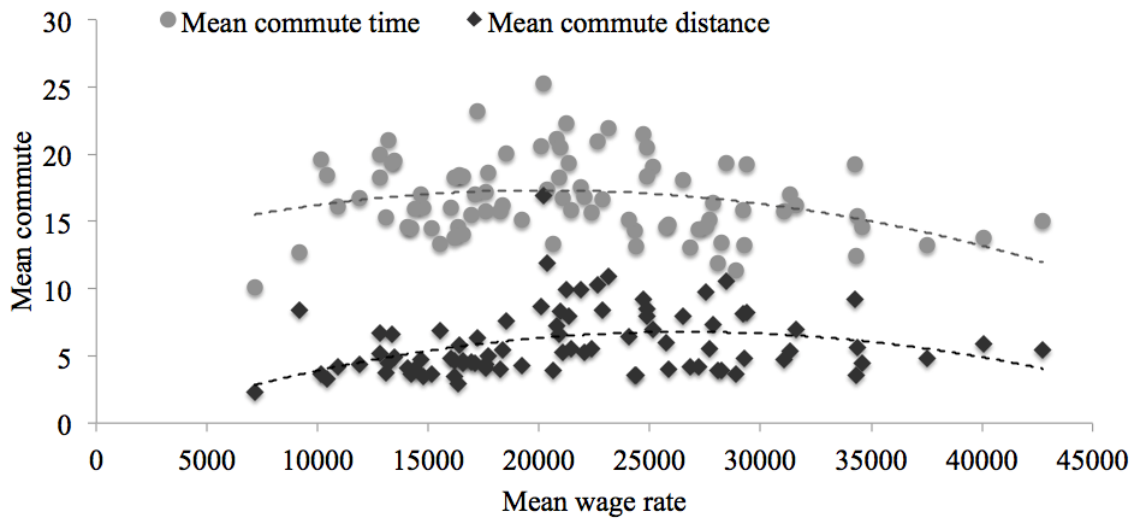


Figure 7. Mean commuting distance/time vs. tract's mean wage rate in 1990.

The largely inconsistent trends between the mean commute distance and time were attributable to the variability of mode distributions across tracts of various mean wage rates. It is well-known that travel time is longer for carpool than drove-alone, and even longer for public transits and others. As shown in Table 7, the percentage of commuters by drove-alone tracts was the smallest in the neighborhood of the lowest wage rate (i.e., 61.9 percent in 1990, 62.2 percent in 2000 and 66.5 percent in 2010), and increased gradually to tracts in higher wage rate. In other words, more workers had to use slower transport modes in lower-wage neighborhoods, and thus increased their commute time. Furthermore, as more low-wage workers tended to live in central city with higher densities and more congested roads, even those drove-alone commuters would use more time to travel the same distance and were less likely to convert their shorter distance trips to shorter duration. As discussed previously, a shorter commute distance also reflects less mobility in job search. The double disadvantages were most evident in 2000 when the tracts in the 0-20-percentile wage group spent most time to commute the shortest distance.

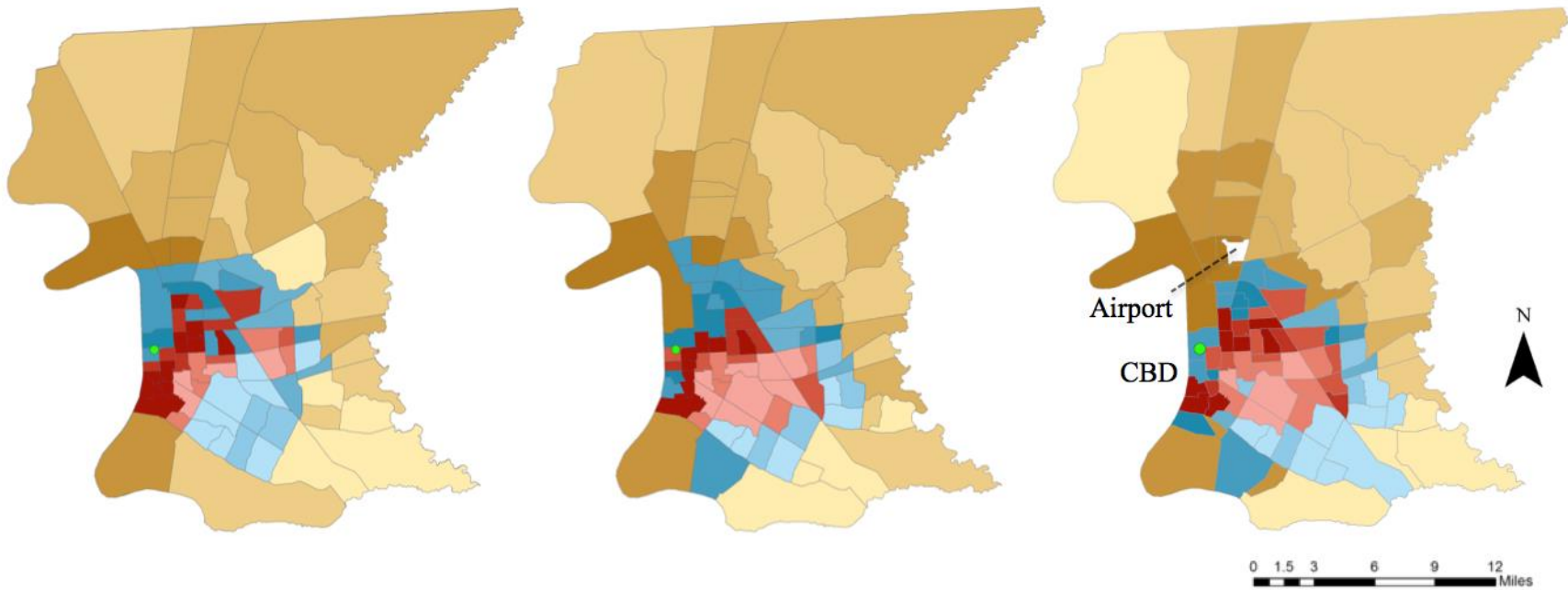
Table 7. Commuting modal splits by tract-level mean wage rate.

<b>Year</b>	<b>Wage percentile group</b>	<b>Drove-alone</b>	<b>Carpool</b>	<b>Public transit</b>	<b>Others<sup>1</sup></b>
1990	0-20	61.91	16.18	4.17	17.74
	20-40	78.37	14.56	1.59	5.48
	40-60	85.28	10.76	0.52	3.45
	60-80	85.06	10.00	0.66	4.27
	80-100	88.07	7.69	0.27	3.97
	All	82.35	11.76	1.29	4.60
2000	0-20	62.17	18.37	5.36	14.11
	20-40	77.77	14.95	2.38	4.91
	40-60	83.19	12.00	0.46	4.35
	60-80	86.21	9.13	0.46	4.20
	80-100	87.00	8.03	0.28	4.68
	All	83.16	11.91	1.40	3.54
2010	0-20	66.50	13.96	4.97	14.57
	20-40	77.72	15.26	2.91	4.11
	40-60	81.85	10.78	2.02	5.35
	60-80	86.13	9.51	0.31	4.05
	80-100	87.47	7.49	0.39	4.66
	All	83.77	11.08	1.75	3.40

<sup>1</sup> Others include taxi, motorcycle, bicycle, walk, etc.

To explore the spatial patterns of commuting and neighborhood's mean wage rate, three bivariate choropleth maps are designed as shown in Figure 8. For each year, tracts are grouped into three categories of about equal frequency (i.e., 33, 66 and 100 percentile) in terms of mean commuting distance, and denoted by distinctive colors. In the meantime, as stated earlier, tracts are also grouped into five categories by mean wage rate percentile, and denoted by each color's darkness. The pattern of mean commuting distance shows a concentric pattern with increasing distance from the CBD for all three time periods,

indicating the consistent significance of downtown Baton Rouge in influencing the commuting pattern. The pattern for mean wage rate displays a contrast between the southeast sector (higher wage) and the rest (including north and a narrow southwest strip with lower wage) in each year. While the general pattern for commuting distance remained concentric over years, the areas falling in each category changed. For example, the zones of short-distance commuting (i.e., 33 percentile marked in red) expanded to the southeast with medium to high income (in lighter red). This highlights that the areas with shorter-distance commuting in 1990 were mostly composed of low-wage earners, but expanded to areas with higher-wage earners. Tracts in the middle (40-60 percentile) wage group were mostly in the north in 1990 (mostly rural at the time), started to shift toward the middle area of Baton Rouge in 2000, and mostly were in the middle in 2010. This may help explain how this is the lone wage group with a trend of shortening commute distance from 1990 to 2010. Also note that areas of the lower wage (0-40 percentile) groups spread out from the central city area over time, and areas for higher wage (60-100 percentile) groups further stretched out from the south to further outskirts of development.



(a)

(b)

(c)

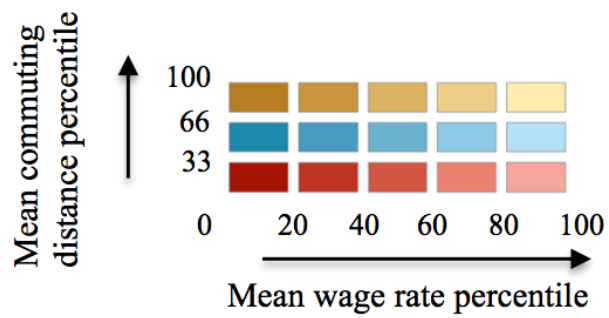


Figure 8. Mean commuting distance and mean wage rate: (a) 1990, (b) 2000, (c) 2010.

Note: Color represents mean commuting distance: red for the shortest, blue for the middle, and brown for the highest. Darkness represents mean wage rate: darker for lower mean wage rate.

## 6.2 COMMUTING PATTERN VS. DISTRIBUTION OF WAGE GROUPS

The above section explores the effect of wage on commute by using the mean wage rate of tracts. Given that a tract's mean wage rate cannot fully represent its real wage distribution pattern where workers of various wage rates reside, this section analyzes the distribution of wage groups across census tracts to obtain more insight into the interaction between commuting and wage.

The CTPP data include the numbers of resident workers in various wage ranges. Different wage ranges were used among the CTPP 1990, 2000 and 2010. We divide workers in tracts into five wage groups (i.e., 0-15k, 15-35k, 35-50k, 50-75k, and 75k+), which is the only feasible classifications to be consistent over time. While all wage groups could be present in one tract with the same mean commute, their relative concentrations (e.g., percentages) vary. Limited by the aggregated data, we cannot single out which wage group(s) commute how much. However, if a certain group is consistently observed to be overrepresented in long-commuting areas and other groups are consistently found to concentrate in short-commuting areas, it is more likely than not that overall the former experiences longer commute than others (i.e., live further away from their jobs). Due to the ecological nature of the CTPP data, the inference from the analysis is merely suggestive and calls for validation by more in-depth analysis of individual data.

Given that workers of all wage groups could reside in the same tract, we formulate a null hypothesis for testing disparities in commuting lengths such as:

$H_0$  (null hypothesis): the proportion of workers (of a certain wage group) living in areas with above-average commute length is the same as that in areas with below-average commute length.



Here, the weighted average commute for the overall population in the study area is used as a benchmark for comparison. We are interested in examining whether a wage group is distributed disproportionately higher in areas of longer commute.

A conventional pooled  $t$ -test may be considered to test the above null hypothesis (Wang and Feliberty, 2010). For easy implementation for a large number of repetitive tests, we choose to use a weighted OLS regression to test the hypothesis (Ikram et al., 2015), where the tract population is used as the weight for appropriate adjustments in the error term. By doing so, a tract with more population is weighted heavier than one with less population. Such an adjustment is not feasible by the conventional pooled  $t$ -test.

Specifically, tracts in the study area are first split into two sets: Set 1 with below-average commute are coded as “Flag = 0”, and Set 2 are above-average tracts coded as “Flag = 1”. Denoting the ratio of a wage group in a tract as  $Y_w$ , the regression model is defined as

$$Y_w = a + b \times Flag \quad (4)$$

The model is estimated by a weighted OLS regression where the total population in a tract defines the weight. The intercept  $a$  is the average % of this wage group in Set 1 (i.e., tracts with below-average commute when Flag = 0). The average % of the wage group in Set 2 (i.e., tracts with above-average commute when Flag = 1) is simply reconstructed as  $a+b$ . The slope  $b$  is the difference between Sets 1 and 2, and its corresponding  $t$  value reveals the statistical significance for the difference.

Table 8. Wage groups in areas above or below the average commuting distance.

Wage group	1990			2000			2010		
	% with below average	% with above average	Difference in %	% with below average	% with above average	Difference in %	% with below average	% with above average	Difference in %
<15k	50.3	38.5	-11.8***	37.7	29.3	-8.4**	28.4	21.6	-6.8*
15-35k	33.1	39.3	6.2***	32.9	36.9	4.0*	30.9	30.3	-0.6
35-50k	9.0	12.7	3.7***	12.5	14.8	2.3*	15.3	17.5	2.2
50-75k	4.7	7.1	2.4**	9.7	12.4	2.7*	13.0	16.4	3.4*
>75k	3.0	2.6	-0.4	7.2	6.5	-0.7	12.4	14.2	1.8

Note: \*\*\* indicates statistically significant at 0.001, \*\* significant at 0.01, \* significant at 0.05.

Table 9. Wage groups in areas above or below the average commuting time.

Wage group	1990			2000			2010		
	% with below average	% with above average	Difference in %	% with below average	% with above average	Difference in %	% with below average	% with above average	Difference in %
<15k	46.2	44.0	-2.2	32.8	35.7	2.9	28.4	23.3	-5.1
15-35k	34.4	37.4	3.0	31.6	37.9	6.3***	28.4	32.9	4.5*
35-50k	10.1	11.3	1.2	14.0	12.9	-1.1	15.6	16.7	1.1
50-75k	5.8	5.6	-0.2	12.0	9.4	-2.6*	13.4	15.0	1.6
>75k	3.6	1.8	-1.8**	9.6	4.0	-5.6***	14.2	12.0	-2.2

Note: \*\*\* indicates statistically significant at 0.001, \*\* significant at 0.01, \* significant at 0.05.

Table 8 and Table 9 report the significance test results of commuting distance and time, respectively. The results list the ratios of each wage group with below-average commute and above-average commute as well as their differences. For example, in 1990, 50.3 percent of lowest-wage workers (i.e., <15k) lived in areas with shorter commute distance than the overall population, while 38.5 percent lived in areas with above-average commute distance. The negative difference (i.e., -11.8) between both ratios is significant at 0.001 level, suggesting that workers in the lowest wage group in 1990 were significantly higher in areas with below-average commute distance, and thus enjoyed shorter commute distance in general. Similarly, we found that workers in the following three groups (i.e., 15-35k, 35-50k, and 50-75k) in 1990 were more concentrated in areas with above-average commute distance, indicating relatively longer commute lengths in these wage groups than the overall population. The highest-wage workers in 1990 appeared to have a slightly higher percentage living in areas with below-average commute distance, but not statistically significant. In a word, the above results demonstrate that workers in the lowest-wage group, in general, commuted significantly less than the overall population, while workers in the following three wage groups commuted significantly more than the overall population. However, no solid conclusions could be drawn for the highest-wage workers due to the insignificant results. Similar pattern was found in 2000 but not as clear as in 1990: only the lowest-wage group tended to concentrate in below-average commute distance areas with statistical significance, and concentrations of other groups in terms of areas of mean commute distance were not statistically significant. In 2010, the tendency of higher concentration of the lowest-wage group workers in areas of below-average commute distance remained significant, but the differences in concentration of other wage groups were not significant or minor (i.e., ratios of the 50-75k wage group in 2010 tended to be slightly higher in tracts of longer commute distance). In general, the

convex shape pattern discovered in previous analysis is not observed in this analysis due to more insignificant results. However, it does highlight the significant shorter commute distance for lowest-wage workers than the average in Baton Rouge 1990-2010, which is largely determined by their limited mobility. If the ecological inference is true that what is true for the group is true for the individual, we can conclude that the lowest-wage workers on average suffer from poor mobility and such disadvantage remained unchanged over time, and relevant policies such as adding more jobs near workers in this group may be considered for improvement.

In terms of commute time, there are several observations to make. First, the difference in concentration of the highest-wage workers was statistically significant in 1990 and 2000 (i.e., more in below-average commute time areas), but such a difference disappeared in 2010. Secondly, in 2000, workers in the 15-35k group were reported to disproportionately live in areas with above-average commute time (significant at 0.001 level). Again, no clear convex shape pattern was found in the association between commute time and wage; however, we do observe less commuting time with statistical significance for the highest-wage workers than the overall workers in 1990 and 2000. Once again, if the ecological inference is valid, the finding may suggest a true advantage in terms of commute time for the highest-wage workers due to their better mobility and job accessibility. Given the ecological nature of the CTPP data, we refrain from further inference.

## CHAPTER 7. WASTEFUL COMMUTING

Although the land use pattern in Baton Rouge explained the commuting variations to some extent, there was still a proportion of variations unexplained (particularly commuting time). Part of the gap could be attributable to the wasteful commuting behavior that individuals do not necessarily optimize their journey-to-work trips as suggested by the spatial arrangements of land uses, i.e., jobs and houses (Hamilton, 1982). Even if individual workers make every effort to minimize their commuting, the outcome may still differ from the minimum total commute collectively for the whole study area.

Wasteful commuting  $T_w$  is the proportion of the average actual commute  $T_a$  over the average required commute  $T_r$ , i.e.,

$$T_w = (T_a - T_r) / T_a \quad (5)$$

Figure 9 outlines the workflow of our analysis. Based on 2006-2010 CTPP, we first replicate the existing approach of measuring wasteful commuting at the zonal (census tract) level, then use the Monte Carlo method to simulate individual locations of resident workers and employment as well as trips between them, and finally calibrate wasteful commuting at the individual level.

### 7.1 MEASURING WASTEFUL COMMUTING AT THE CENSUS TRACT LEVEL

As stated previously, both travel time and distance are used to measure wasteful commuting. For demonstration of the methods, here only travel time is mentioned. We adopt the popular Linear Programming (LP) technique to derive optimal commute. Commonly referred to as the transportation problem, the problem is to solve the optimal journey-to-work flows between origin and destination zones in order to minimize the

average travel time (Hitchcock, 1941; Horner and Murray, 2002; Taaffe et al., 1996), such as presented in Equation (6) – (9).

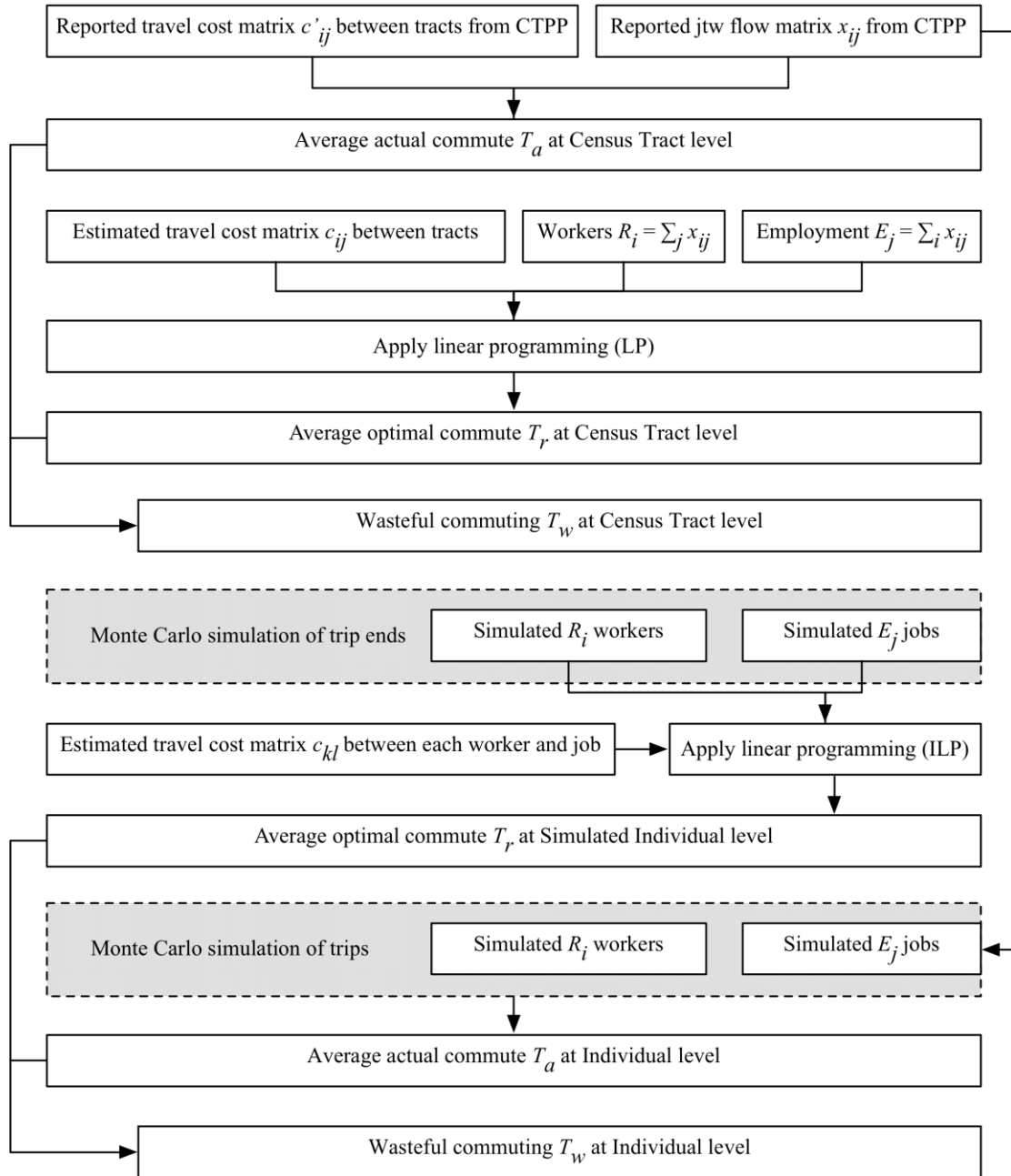


Figure 9. Workflow of measuring wasteful commuting at the zonal and individual levels.

$$\text{Minimize} \quad T_r = \sum_i \sum_j (c_{ij} x_{ij}) / N \quad (6)$$

$$\text{Subject to:} \quad \sum_j x_{ij} = R_i \quad (7)$$

$$\sum_i x_{ij} = E_j \quad (8)$$

$$x_{ij} \geq 0 \quad (9)$$

where  $c_{ij}$  is the commuting time from zone  $i$  to zone  $j$ ;  $x_{ij}$  is the number of commuters living in zone  $i$  and working in zone  $j$ ;  $R_i$  represents the number of commuters living in zone  $i$ ;  $E_j$  represents the number of commuters working in zone  $j$ ;  $N = \sum_i \sum_j x_{ij}$  is the total number of commuters.

Equation (6) defines the objective function of minimizing the average commuting time, which is subject to three constraints. Equation (7) ensures that all journey-to-work flows originating from one zone satisfy the total number of commuters living in that zone. Similarly, Equation (8) limits all journey-to-work flows ending in one zone to the total number of commuters working in that zone. Equation (9) restricts the journey-to-work flow matrix  $x_{ij}$  to be non-negative values. The resulting  $T_r$  returned by the objective function represents the average required commuting time, suggested by the spatial arrangement of homes and jobs. Comparing actual commute  $T_r$  to actual commute  $T_a$ , Equation (5) measures the wasteful commuting rate.

In implementation, intrazonal travel distance  $c_{ii}$  is approximated as the radius of a circle with the same area size as a zone (Frost et al., 1998; Horner and Murray, 2002), and the corresponding intrazonal travel time is obtained by simply assuming a constant travel speed of 25 mph through the distance. The interzonal travel distance (time)  $c_{ij}$  is calibrated between the centroids of census tracts by the shortest network path, and then modified by

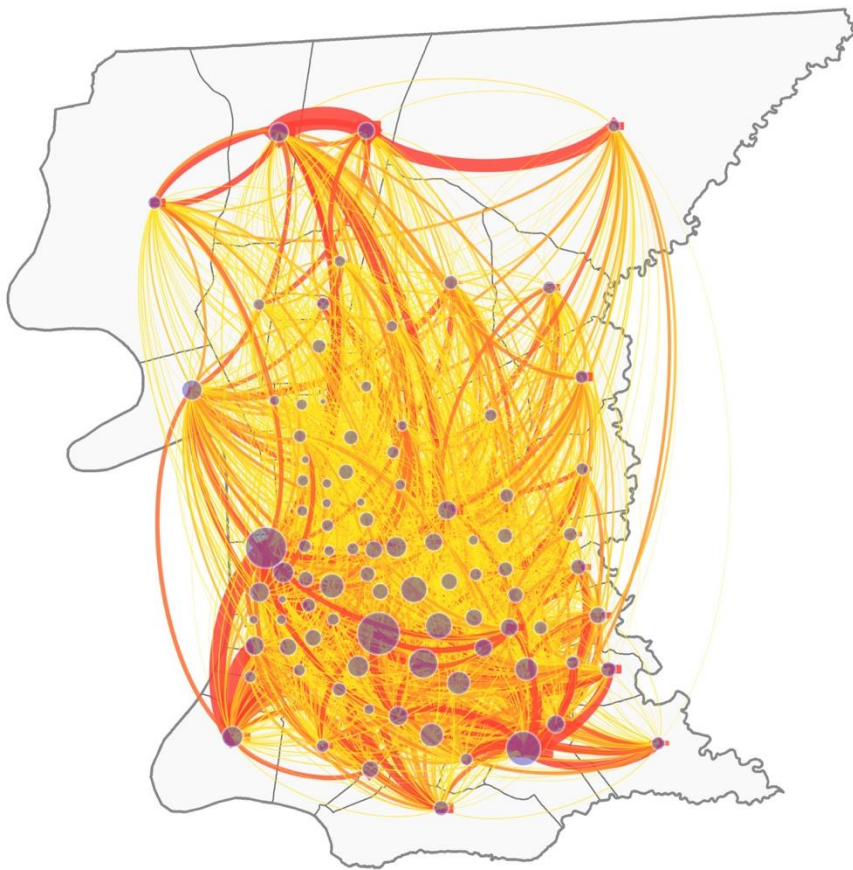
adding the intrazonal components (distance or time) at both the origin and destination zones.

Solving the zonal-level LP as defined in Equations (6) – (9), we obtain the optimal commuter flow matrix  $x_{ij}$ , and then the average minimum commute defined in Equation (6). The average minimum commuting time in the study area is 6.61 minutes, and the average minimum commuting distance is 3.44 miles. Note that the intrazonal travel times and distances are not zero here and vary with tract area sizes. As a result, the optimal commuting pattern has only 24.4 percent (i.e., 44,590/182,705) within-tract commute trips when travel time is used, and 19.5 percent (i.e., 35,597/182,705) within-tract trips when distance is used.

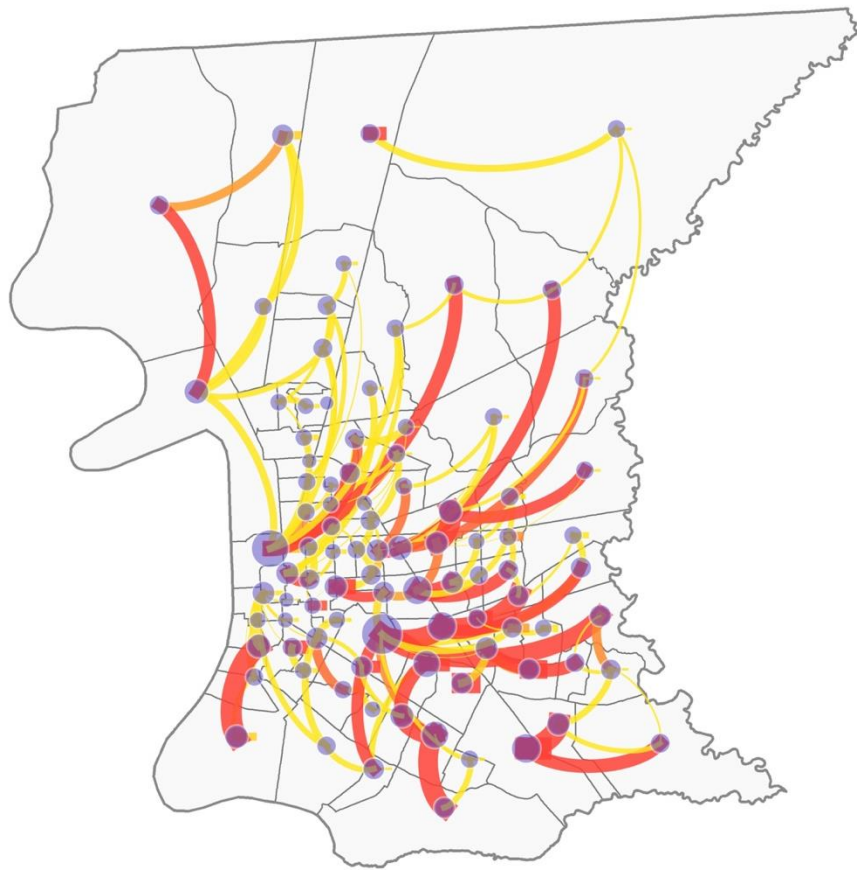
Figure 10 provides a visual comparison between actual and optimal commuter flows at the census tract level. Note that trips are substantially trimmed after optimization, and mostly are within tracts and between tracts in proximity.

Based on reported journey-to-work flow volumes and corresponding mean travel time between tracts from the CTPP data, we obtained 19.26 minutes for the average actual commuting time. No mean travel distance is reported in the survey. As argued previously, reported travel time from a survey could include reporting errors and respondents might not be representative of the areas they reside. Furthermore, as the concept of wasteful commuting emphasizes the gap between actual and optimal commute lengths, it makes more sense to also estimate actual commute time (or distance) through network analysis since the optimal commute is an estimated measure. For comparison, we obtained the estimated travel time (distance) for all commute flows, and then average estimated commute time of 12.76 minutes and average estimated commute distance of 7.42 miles.





(a)



(b)

Figure 10. Tract-level commuting networks: (a) actual reported flow, and (b) optimal flow.  
[Line width is proportional to flow volume, and bubble size represents total throughput at a tract]

With all the above results in place, wasteful commuting was calculated according to Equation (5) at the census tract level. Based on Table 10, wasteful commuting time was 65.68 percent by comparing actual reported time with optimal time, and dropped to 48.20 percent by comparing estimated time with optimal time. In terms of distance, wasteful commuting was 53.64 percent. The extent of wasteful commuting when using estimated time (48.20 percent) is more in line with that in distance (53.64 percent) as distance is also estimated from the road network.

Table 10. Summary of actual, optimal and wasteful commuting in Baton Rouge 2010.

		<b>Average Commuting Time (min)</b>	<b>Average Commuting Distance (mile)</b>
Census tract level			
Actual	Reported	19.26	NA
	Estimated	12.76	7.42
Optimal		6.61	3.44
Wasteful	Reported vs. Optimal	65.68%	NA
	Estimated vs. Optimal	48.20%	53.64%
Simulated individual level			
Actual	Estimated	12.65	7.63
Optimal		4.75	2.71
Wasteful	Estimated vs. Optimal	62.45%	64.48%

Note: NA means not available.

## 7.2 MEASURING WASTEFUL COMMUTING AT THE SIMULATED INDIVIDUAL LEVEL

Similar to the LP at the zonal level, the formulation of optimal commute at the individual level utilizes the Monte Carlo simulation of resident workers and jobs. Index the

locations for simulated individual resident workers and jobs as  $k$  and  $l$ , respectively. The total number of simulated workers is the same as that of simulated jobs, denoted by  $n$ . The optimization problem is

$$\text{Minimize} \quad \sum_{k=1}^n \sum_{l=1}^n (c_{kl} f_{kl}) / n \quad (10)$$

$$\text{Subject to:} \quad \sum_{l=1}^n f_{kl} = 1 \quad (11)$$

$$\sum_{k=1}^n f_{kl} = 1 \quad (12)$$

$$f_{kl} = 1 \text{ when a trip from } k \text{ to } l \text{ is chosen, } 0 \text{ otherwise} \quad (13)$$

where  $c_{kl}$  is the estimated travel time from resident worker location  $k$  to job location  $l$ , and  $f_{kl}$  indicates whether a journey-to-work flow is chosen by the optimization algorithm (= 1 when chosen and 0 otherwise). The objective function (10) is to minimize the average commute time of  $n$  simulated commuters. Equations (11) and (12) ensure that each worker can be assigned to one unique job and vice versa. Since the variable  $f$  is a binary integer, it is an integer linear program (ILP) problem.

The result from the above ILP is the average minimal commuting,  $T_r$ . As explained previously, if the estimated travel time for a Monte Carlo simulated trip between two individual points  $p$  and  $q$  is  $c_{pq}$ , the average estimated commuting time  $T_a$  in the simulated pattern is  $T_a = \sum_{p,q} c_{pq} / n$ . Since both the origins and destinations are individual points and do not involve any area configuration, both optimal commute and existing commute are estimated from the point-to-point OD trips. The approach is thus independent from the zonal effect or MAUP.

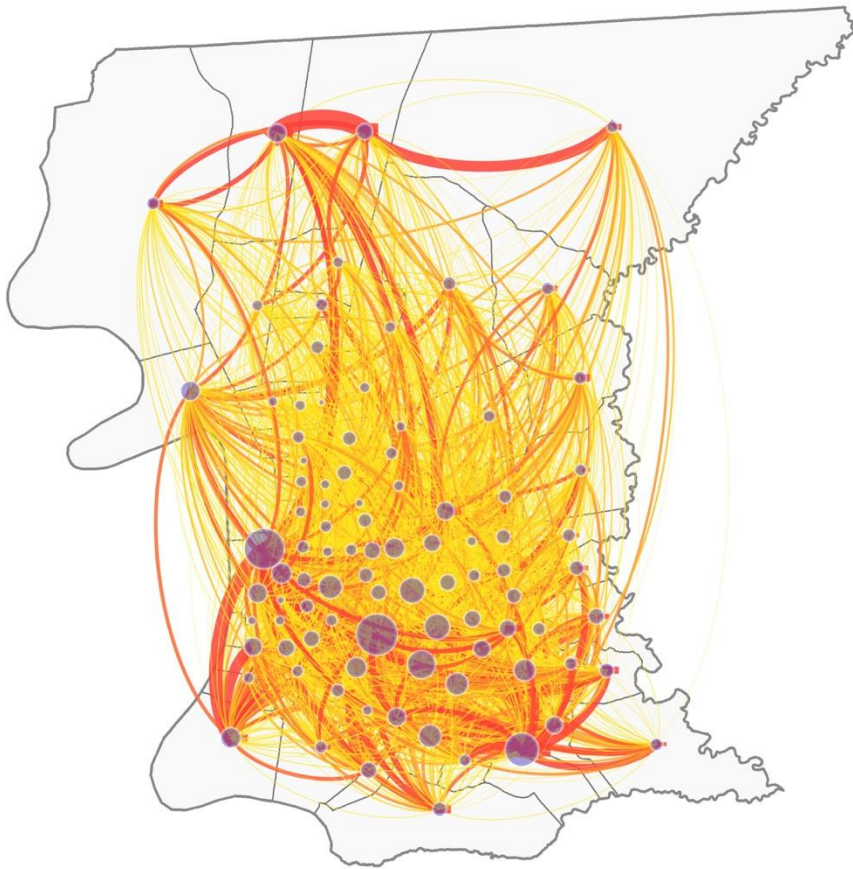
To mitigate the scale effect in the zonal level analysis, we solved the integer linear programming (ILP) problem defined in Equations (10) – (13) for simulated individual commuters. As discussed previously, the total number of simulated commuters (or resident workers or jobs)  $n$  by the Monte Carlo approach needs to be determined by balancing accuracy and computational efficiency. Based on a series of experiments with different sample sizes, we set the value of  $n$  to be 3,565, which was limited by the computation of all possible OD cost matrix (i.e., 3,565\*3,565 pairs) in ESRI ArcGIS 10.1 in a PC environment (i.e., Intel Core 2 Quad 2.4 GHz CPU with 4GB memory and 500GB hard disk). The ILP yielded average minimum commuting time and distance at the simulated individual level as 4.75 minutes and 2.71 miles, respectively. Both are significantly lower than the optimal commute time and distance obtained at the census tract level. This difference validates the impact of zonal effect on the measure of wasteful commuting as pointed out by Hamilton (1989).

Next we need to estimate travel time (distance) for the simulated trips that are consistent with the actual journey-to-work flow pattern. As discussed previously, the OD trips based on the Monte Carlo simulation are randomly paired individual locations of resident workers and jobs, but the total number of simulated commuters between two tracts  $i$  and  $j$  is capped proportionally to the actual journey-to-work volume such as  $(n/N)x_{ij}$ , where  $n = 3,565$  and  $N = 182,705$ . By doing so, zonal-level trips are disaggregated into individual trips. Based on the simulation results, the average estimated commuting time and distance are 12.65 minutes and 7.63 miles, respectively. Both estimations are very close to those obtained at the census tract level. In other words, the disaggregation does not

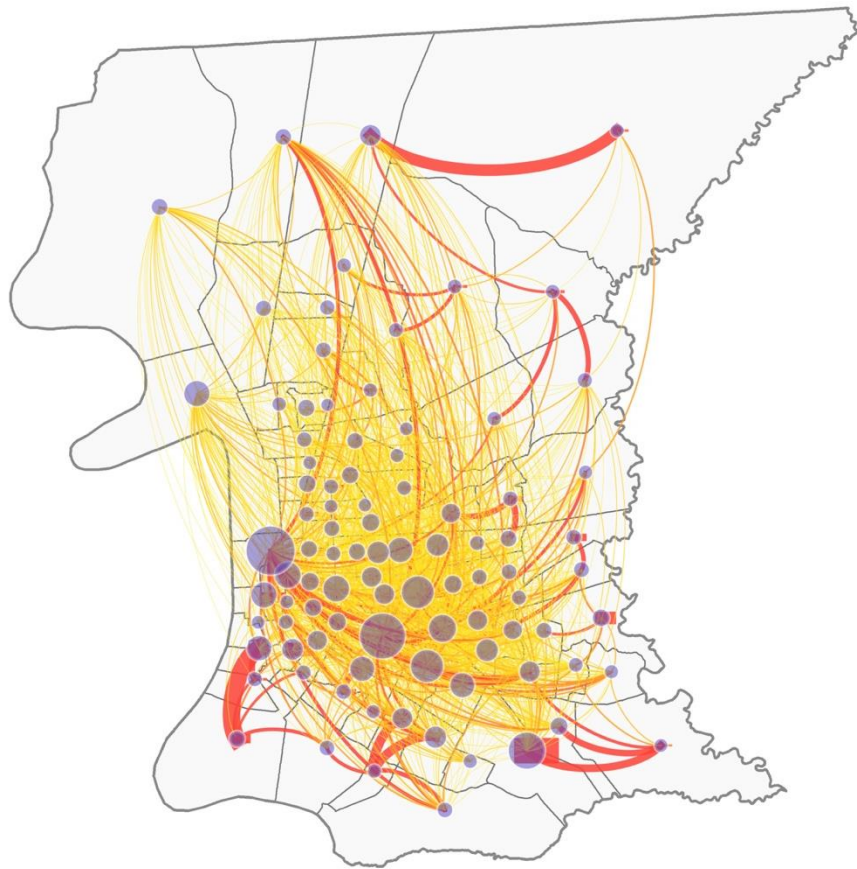
alter the estimated commuting amounts significantly, and the difference mainly lies in the minimum (required) commuting.

The visualization of networks at the simulated individual level would be too crowded to see any pattern. We aggregated both simulated flows and optimized flows into the census tract level, shown in Figure 11a and Figure 11b, respectively. Since the simulated flows at the individual level were intentionally designed to be proportional to the actual flows, the same pattern is observed between Figure 10a and Figure 11a, confirming that our simulation of trips worked well. In contrast to Figure 10b with a simpler pattern, Figure 11b shows the optimal commute flows at the census tract level that were aggregated back from the individual optimal pattern, which is far more complex. Individual workers are now free to swap houses for individual job locations, instead of being confined to a tract centroid for a group of workers (or a group of jobs). Therefore, the flexibility enables more choices in the optimized pairing between workers and jobs, and further brings down the total (average) minimum commuting. Figure 11b also shows far more interzonal trips as individual workers are more likely to be paired with individual jobs in adjacent tracts instead of within the same tracts (see Figure 10b), and thus a more realistic optimization pattern.

Measured at the simulated individual level, we obtained 62.45 percent wasteful commuting time and 64.48 percent wasteful commuting distance. Both are higher than those estimated at the census tract level. The results are also reported in Table 10.



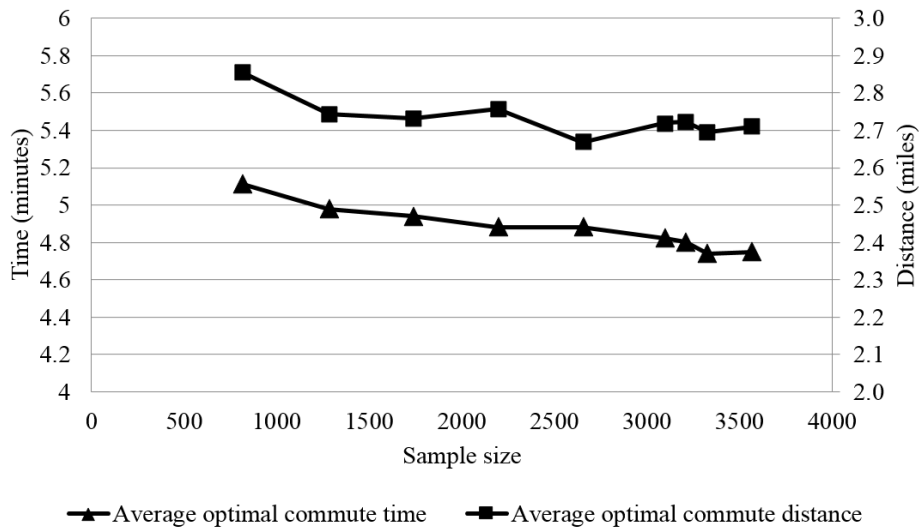
(a)



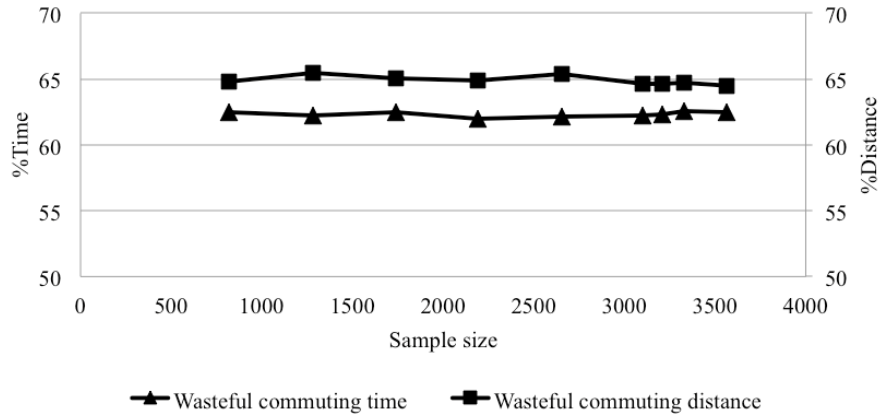
(b)

Figure 11. Aggregated individual-level commuting networks: (a) simulated flow and (b) optimal flow.  
[Line width is proportional to flow volume, and bubble size represents total throughput at a tract]

An issue regarding the sensitivity of simulation sample size merits some discussion here. The cap of  $n=3,565$  simulated commuters was set due to our computation limitation in calibrating of the large  $n \times n$  OD cost matrix for the ILP. Here we experimented with nine sample sizes from 820 to 3,565. Results for average optimal commute (time and distance) and corresponding wasteful commuting percentage are shown in Figure 12a and Figure 12b, respectively. As we increased the sample size, the average optimal commute, both in time and distance, tended to initially decrease and then stabilize after the sample size reached about 3,000. Even for smaller sample sizes (e.g., when  $n$  increased from 820 to 1,282), the changes in both measures were minor (i.e., 0.13 minutes for optimal commuting time, and 0.1 miles for optimal commuting distance). For larger sample sizes (e.g., when  $n$  increased from 3,256 to 3,565), the changes in the two measures were minimal (i.e., 0.004 minutes for time and 0.003 miles for distance). A similar trend can be said on the resulting percentages of wasteful commuting: the wasteful commuting time began to converge around 62 percent and the wasteful commuting distance tended to converge around 64 percent after the sample size reached 3,000. This confirms that the sample size of 3,565 commuters was a sound choice for the study area.



(a)



(b)

Figure 12. Sensitivity of simulation sample size: (a) optimal commute, (b) wasteful commuting.

### 7.3 DISCUSSION ON DECOMPOSING WASTEFUL COMMUTING

Based on the results summarized in Table 10, Figure 13 illustrates various measures of average commuting time in the study area. The reported average time from survey stood at the highest value of 19.26 minutes. This may well be the amount of time experienced by commuters in general. However, the extent of wasteful commuting is derived when the actual commuting is compared to the minimal (optimal) commuting that is often based on estimation. The concept of wasteful commuting was initially proposed for the purpose of assessing the gap between what would be possible collectively for a city given its land use pattern and what individuals actually do. Therefore, it seems fairer to compare actual and optimal commute time by measuring both in estimated time from road network. Our average estimated commuting time (drove-alone) of 12.76 minutes was much shorter than the reported time of 19.26 minutes because the latter was affected by many factors such as commuters by slower modes, traffic congestion or even mental time that survey respondents might have included to account for parking and others. As the CTPP does not



report commuting distance data, this issue is not relevant when distance is used to measure commuting length.

The conventional LP approach at the zonal level yielded an average minimal (optimal) commuting time of 6.61 minutes. By simulating individual locations of resident workers and jobs and also the individual trips linking them, our research returned an average minimal commuting time of 4.75 minutes. When the zonal-level approach is used, resident workers and jobs are grouped together in zones (e.g., tract centroids), and the free swap of homes permitted by the optimization are between zones. In our approach at the simulated individual level, the optimization permits resident workers to freely swap homes with individual locations, leading to a large number of optimal commuting trips that are much shorter and interzonal. The individual level approach is not only more accurate for its sharper resolution in estimating trip lengths but also generates more realistic optimal commuting pattern.

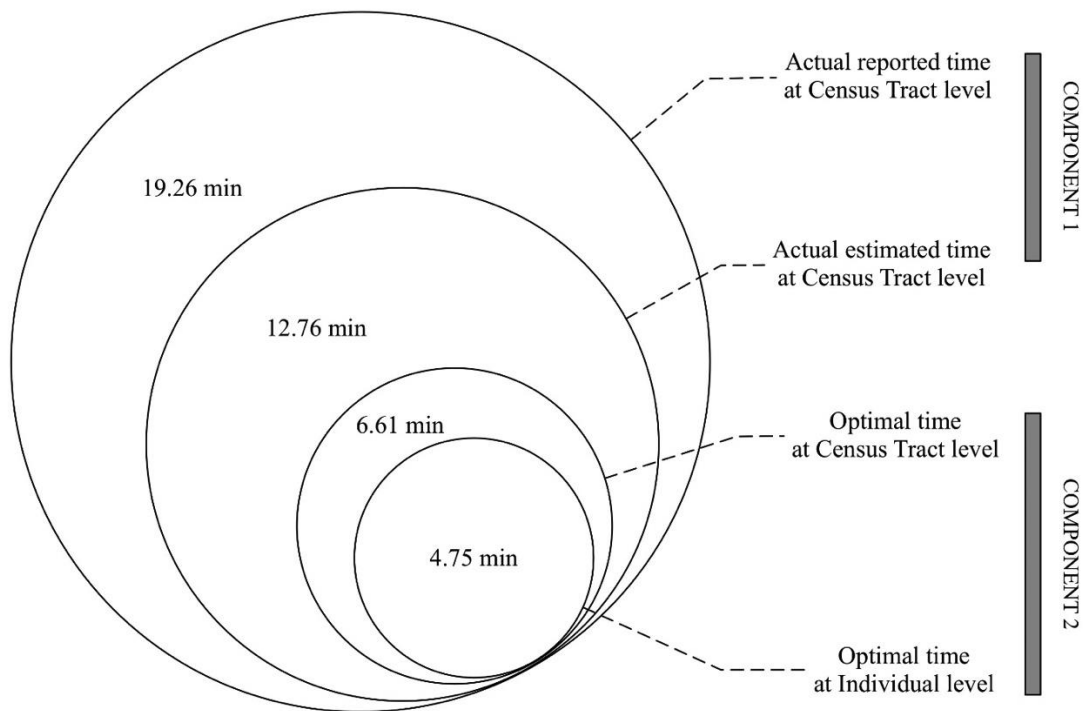


Figure 13. Various measures of average commuting.

Figure 14 further clarifies the two components of false estimation of wasteful commuting. When reported commuting time is used as a benchmark, the wasteful commuting stands as high as 65.68 percent at the zonal level. When estimated commuting time is used as a new benchmark, the wasteful commuting comes down to 48.20 percent at the zonal level. That is to say, using reported commuting time implies an overestimation of 17.48 percent wasteful commuting that is attributable to people using slower transport modes or getting caught in traffic, which a planning scenario of freely swapping house would not help. The 17.48 percent overestimation is termed “component 1” in miscalculation. By disaggregating zonal-level commuting patterns to simulated individuals, the average optimal commuting time is reduced and leads to a higher percentage of wasteful commuting (i.e., climbing back to 62.45 percent from 48.20 percent). That is to say, the zonal level approach causes an underestimation of wasteful commuting by 14.25 percent, termed “component 2” in miscalculation.

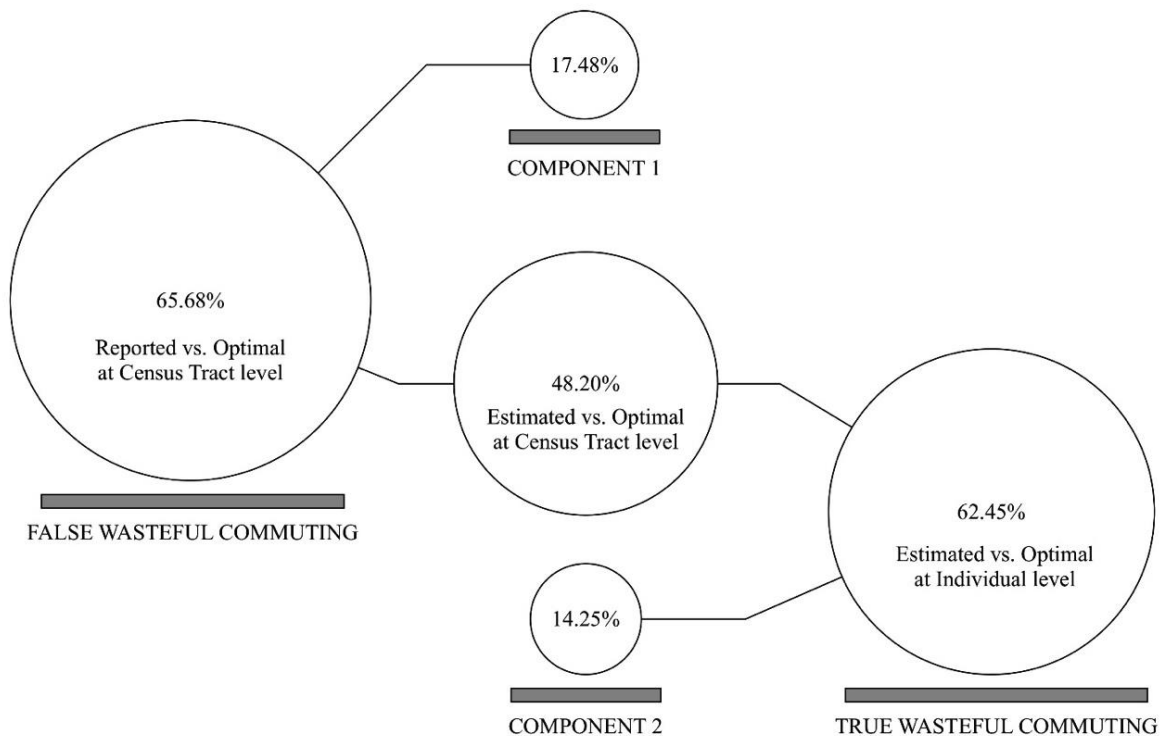


Figure 14. Decomposing wasteful commuting.

In summary, the reported commuting time inflates the wasteful commuting measure by 17.48 percent, and the zonal effect underestimates it by 14.25 percent. The two components bias the estimation in opposite directions and offset each other to a large extent. The traditional approach adopted in most literature yields 65.68 percent wasteful commuting, very close to 62.45 percent obtained in our approach. However, “two wrongs do not make a right.” The debate of wasteful commuting should not be about who gets the specific percentage close, rather about the scientific soundness in the means by which one reaches that percentage.

When measured in distance, estimation error caused by component 1 is absent. The zonal level analysis generates 53.64 percent wasteful commuting. The simulated individual level analysis yields a lower average minimal distance, and thus increases the wasteful commuting to 64.48 percent, in line with the 62.45 percent wasteful commuting time.

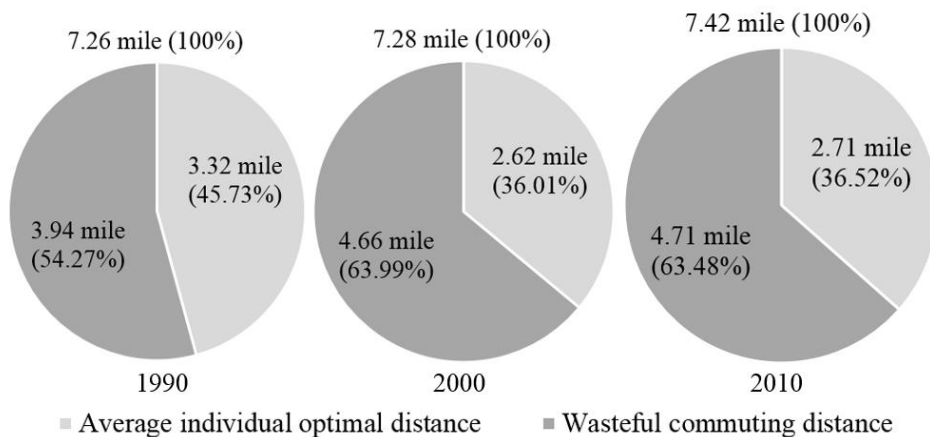
This study also sheds lights on the choice of time or distance in measuring wasteful commuting. Some studies argue that travel time is a more appropriate estimate of travel cost and an important determining factor of travel behavior (Buliung and Kanaroglou, 2002; Gordon et al., 1991; Wachs et al., 1993). In this study, difference in the results for time and distance is insignificant (when estimated time is used). The only complexity is whether to use reported commuting time as a benchmark for actual commute. If we define excessive time in using public transit or other slower modes and delayed time in congestion as “wasteful”, reported time would be an adequate choice.

#### 7.4 TEMPORAL TRENDS OF WASTEFUL COMMUTING

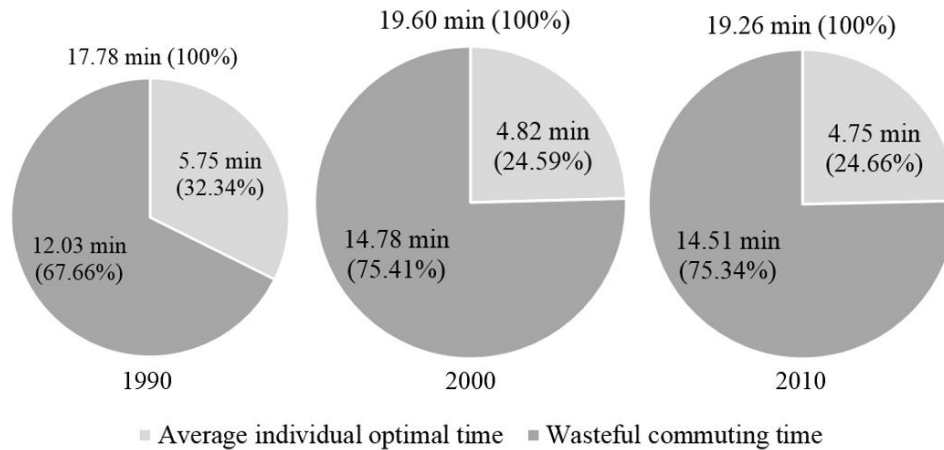
Similar to 2010, we also measure the wasteful commuting for 1990 and 2000. Figure 15 summarizes the results on wasteful commuting in Baton Rouge 1990-2010. Once again, the average commute distance in the study area increased steadily from 1990 to 2000 and again to 2010; and the average commute time increased from 1990 to 2000 but dropped slightly to 2010.

As the concept of wasteful commuting is proposed mainly to assess the potential of commuting reduction given the land use pattern of a city, our discussion here focused on the results in terms of commute distance.

The minimum (required) commute was 3.32 miles in 1990, and dropped to 2.62 in 2000 and inched up slightly to 2.71 in 2010. It suggested that land uses in Baton Rouge might have changed in a way toward more efficiency in terms of commuting need from 1990 to 2000 (e.g., improved proximity between jobs and resident workers in general), and stayed largely stable till 2010. However, the resident workers did not take advantage of the change, and actually increased their trip lengths on average from 7.26 in 1990 to 7.28 in 2000 and then again to 7.42 miles in 2010. This led to the rise of wasteful commuting distance from 54.27 percent in 1990 to 63.99 percent in 2000, and stayed at 63.48 percent in 2010. Many factors may have contributed to this trend of largely increasing wasteful commuting, such as an increasing female labor participation rate (and thus more multi-worker households) and a small increase in carpool modal share from 1990 to 2000 (Table 2).



(a)



(b)

Figure 15. Wasteful commuting in Baton Rouge 1990-2010: (a) distance, (b) time.

### 7.5 AN EXTENSION TO WASTEFUL COMMUTING

The assumption in measuring wasteful commuting is that people could freely exchange their homes and jobs in a city. It allows us to specifically focus on the spatial separation between homes and jobs (i.e., land use layout) by simply relocating resident workers without altering existing land use layout such as building new houses or adding new jobs. However, it becomes increasingly difficult to apply this simplistic assumption to current urban systems, where jobs (and residents) are more decentralized and social inequalities are more common. For example, it would be unfair or impossible to perform a switch between a stockbroker who lives in the suburbs works downtown and a domestic worker in the inner city (downtown) works in the suburbs. Beside this extreme example there is enough specialization in society that such an assumption of equality of jobs and workers can lead to erroneous trip patterns. To make this topic more meaningful, a possible extension is to consider more factors beyond land use in the assumption. For instance, we may further constrain the relocating process to those resident workers of comparable income. Likewise, other factors such as occupation, multiworker household, and vehicle ownership may be taken into

account if such data are available so that we can obtain a more practical extent of wasteful commuting.

For illustration, we designed an example to measure wasteful commuting in Baton Rouge in 2010 by adding a constraint of comparable income in the assumption, given the data availability in CTPP (e.g., number of workers/jobs in a wage range in each tract). We first grouped resident workers and jobs into different wage strata and then repeated the above process for each wage group. For example, Equation (14) defines the tract-level optimal commuting for workers of a particular wage group  $g$ , where  $x_{ij}^g$  is the number of commuters who are in wage group  $g$ , live in tract  $i$  and work at jobs of the same wage group  $g$  in tract  $j$ ;  $c_{ij}^g$  is the corresponding commuting time between them;  $n^g$  is the total number of commuters of wage group  $g$ ; and refer to Equations (7) – (9) for the constraints (note, number of workers  $R_i$  is now changed to  $R_i^g$  and number of jobs  $E_j$  to  $E_j^g$ ). Similarly, Equation (15) formulates the individual-level optimal commuting for workers of a specific wage group  $g$ , and refer to Equations (11) – (13) for constraints. As formulated in Equation (16), the overall optimal commuting for commuters of all wage groups is the weighted average of  $T_r^g$  of various wage groups, where  $wg$  is the number of wage groups defined.

$$\text{Tract level: } T_r^g = \min \left\{ \sum_i \sum_j (c_{ij}^g x_{ij}^g) / n^g \right\} \quad (14)$$

$$\text{Individual level: } T_r^g = \min \left\{ \sum_{k=1}^{n^g} \sum_{l=1}^{n^g} (c_{kl}^g f_{kl}^g) / n^g \right\} \quad (15)$$

$$\bar{T}_r = \sum_{g=1}^{wg} n^g T_r^g / \sum_{g=1}^{wg} n^g \quad (16)$$

The proposed simulation process could be applied here to measure wasteful commuting of each wage group at individual level, but its value and accuracy could be compromised without adopting additional data. Specifically, without better knowledge, a random distribution in space

(e.g., tracts) is reasonable for the overall resident workers, but not necessarily applicable to subgroups of workers (e.g., wage groups) given the fact that workers of all wage groups could be present in the same census tract. For more accurate and meaningful estimates, one possible way is to define the spatial extents of each wage group (e.g., where they live and work) based on other data sources such as house price data. Without these auxiliary data in place, instead, our example here focused on measures at census tract level.

Table 11 reports the results for commuting time (distance is not reported). We divided workers (and jobs) into the same five groups as in section 6.2. Actual commuting time was measured by network travel time, and the aforementioned convex pattern was observed again; it increased from the low wage group and peaked at the medium, and then declined towards the high wage group. Notably, the low and high wage group workers, on average, had shorter commute time than the general workers, while the other three groups commuted longer time than the overall workers. This appears consistent with findings shown in Table 9, although the difference in % between below-average and above-average is not significant in some groups. Optimal commuting was found to be stable across wage groups at 6.61 minutes, the same as the general commuters. That is to say, existing land use layout in Baton Rouge in 2010 tended to be fair for workers of different wage levels, but some groups (e.g., lower-medium, medium, and upper-medium) chose to commute longer than what was suggested, and thus incurred wasteful commute. The wasteful commute was detected to vary slightly across wage groups as a result of their differentiation in actual commute. The weighted average percentage was reported to be 48% for workers of all wage groups, almost the same as the result reported in Table 10 where no comparable income assumption is appended. The diversity of resident workers/jobs in each census tract might play a role in smoothing the variation of wasteful commuting across wage groups and thus did not drive up the weighted

average percentage when homogeneous wage level was imposed. In sum, even though similar percentages were obtained after adding additional constraint, this line of research still needs more investigation—it is not the specific percentage matters, rather the means by which one reaches that percentage.

Table 11. Wasteful commuting breakdowns by wage groups in Baton Rouge in 2010.

<b>Wage Group</b>		<b>Actual Commuting (min)</b>	<b>Optimal Commuting (min)</b>	<b>Wasteful Commuting</b>
Low	< 15k	12.24	6.6078	0.46
Lower Medium	15-35k	12.99	6.6077	0.49
Medium	35-50k	13.33	6.6103	0.50
Upper Medium	50-75k	13.04	6.6077	0.49
High	> 75k	12.37	6.6070	0.47
Total		12.76	6.6081	0.48



## CHAPTER 8. CONCLUSIONS

This dissertation aims at detecting the temporal trends of intraurban commuting pattern (i.e., commuting distance and time) and efficiency (i.e., wasteful commuting) in Baton Rouge, Louisiana between 1990 and 2010 and understanding the observed pattern by a spatial factor—land use and a nonspatial factor—wage rate. Monte Carlo simulation method is proposed in this dissertation so as to measure commuting length at the most disaggregate level—the individual level—for solving the aggregation error and scale effect, which are commonly encountered in existing studies. Major data source employed is the CTPP data (1990, 2000, and 2006-2010) from the U.S. Census Bureau, which describes commuting characteristics from three parts: part 1 on residential places, part 2 on workplaces, and part 3 on journey-to-work flow.

This chapter summarizes the major findings from previous analyses as well as the contributions, limitations and future steps of this research. As mentioned, the research objectives of this dissertation include:

- designing a simulation-based approach to more accurately measure commuting length so as to mitigate the aforementioned issues that have been central to the study of commuting;
- applying the proposed approach to detecting the intraurban commuting pattern (in both distance and time) in Baton Rouge, Louisiana over time (between 1990 and 2010);
- investigating how a spatial factor—land use—influences the discovered commuting pattern;
- examining the impact of a nonspatial factor—wage rate—on the detected commuting pattern;
- measuring commuting efficiency, i.e., wasteful commuting behavior and its temporal trends.

Accordingly, Chapter 4 explains the proposed Monte Carlo simulation approach; Chapter 5 detects the temporal trends of commuting pattern in both distance and time and then investigates the relationship between commuting and a spatial factor—land use; Chapter 6, on the other hand, examines the impact of a nonspatial factor—wage rate—on shaping the commuting pattern; Chapter 7 measures the commuting efficiency—wasteful commuting as well as its change over time. Major findings are summarized below.

### **Major findings**

First, as suggested by the classic urban economic model, people would commute longer to trade for more spacious housing in their residential choices. As income rise and transportation infrastructure improves over time, commuting may become increasingly lengthier. This research indicates that indeed the mean commuting distance steadily increased over time, and thus workers in general moved farther away from their jobs in order to get better housing or maximize their earnings. Mean commuting time rose along with mean commuting distance during 1990-2000, but went the opposite direction by dipping slightly during 2000-2010. The gap between the two in 2000-2010 was attributable to a rising modal share of drove-alone (particularly in the low-wage group) that was faster.

Second, in urban studies, there has been a long tradition of attempts to explain intraurban variability of commuting by land use patterns. It is fair to say that results from existing studies (most on large cities) have been less than overwhelmingly convincing. This research reports that the mean commuting distance variations can be well explained by distance from the CBD, job-housing balance ratio, and even more than 90 percent by the job proximity index. The models on mean commuting time also show improvement over existing studies. This result contradicts the finding of Giuliano and Small (1993) that urban land use had little impact on commuting, as they

used a zonal required commuting that could not necessarily correlate well with the actual commuting in their model. The better results may be attributable to improved measure of commute distance and a moderate city size in this study. This finding lends support to the effectiveness of planning policies that are aimed at trip reduction by improving jobs–housing balance and job proximity.

Third, the aforementioned tradeoff behavior between commuting and housing played out differently in housing choices among households from various wage groups. The analysis of commuting variability across neighborhoods with different mean wage rates demonstrates that workers in areas with higher mean wage rates initially tended to commute further (in distance), but the trend was reversed toward less commuting in areas with the highest wage rates. The convex shape pattern is used to characterize neighborhoods in terms of the response of mean commuting distance to rising mean wage rate. The pattern of mean commute time was hardly consistent over time due to the variability of mode distributions across tracts of various mean wage rates. Given that a tract’s mean wage rate cannot fully represent its real wage distribution pattern where workers of various wage rates reside, in addition, we examined the commuting patterns vs. distribution of wage groups across tracts as an analysis complementary to the above one. This analysis found no clear convex shape pattern in terms of both commute distance and time in 1990-2010; however, it highlighted the lowest-wage workers with shorter commute distance than the general workers (with statistical significance) as well as the highest-wage workers with less commute time (with statistical significance). The economic commute distance in the lowest-wage workers are found to be largely associated with their poor transport mobility, while highest-wage workers are the groups who truly enjoy the efficient commute time. This finding may help target policy-makers on specific socio-demographic groups to improve the efficiency of planning and policies.

Finally, this research identifies two contributors resulting in the miscalculation of wasteful commuting, which captures the potential for a city to reduce its overall commuting given its spatial arrangement of homes and jobs. Specifically, studies usually rely on survey data such as the CTPP to define actual commute time, and measure the optimal commute at an aggregate zonal level by linear programming (LP). This research argues that reported commute time by respondents tends to overestimate actual commute length as it includes reporting errors, travel time by slower transportation modes (e.g., public transits, bicycling, walking and others) and delayed time due to congestion. The zonal level analysis of optimal commute also suffers from the scale effect. Both contribute to bias in the measurement of wasteful commuting. This research proposes to measure wasteful commuting at the most disaggregate level by simulating trip ends, i.e., individual resident workers (O) and individual jobs (D) within zones (e.g., census tracts), in order to mitigate the zonal effect. It also computes estimated commute distance and time for actual journey-to-work trips as a new benchmark for existing commuting. In addition, the new formulation of integer programming also has good potential for wider adoption in modeling the optimal commuting pattern of individual trip makers. The resulting estimates of wasteful commuting are largely consistent between measures in time and distance. A temporal analysis on wasteful commuting changing pattern in this study indicates that Baton Rouge in its entirety experienced an increase of wasteful commuting from 1990 to 2000 in both commute distance and time, and stayed at about the same levels toward 2010. This indicates that the land use configuration changed in such a way that jobs were collectively moved closer to residences and thus became better balanced from 1990 to 2000, but the resident workers did not take advantage of that and incurred more wasteful commuting. The trend of rising wasteful commuting was largely halted between 2000 and 2010. The economic downturn beginning in 2008 might be one reason underlying the new trend (Horner

and Schleith, 2012). The low temporal resolution data (i.e., five-year pooled 2006-2010 CTPP) prevent us from validating this speculation.

On the methodological front, this research proposes a Monte Carlo simulation-based approach for improved modeling of commuting patterns. Granted, a more disaggregated data (e.g., block level) would incur minor aggregation error, but such detailed data in terms of both spatial and temporal resolution are not always available in commuting studies. Given the more widely available zonal-level commuting data (e.g., CTPP in the United States), the proposed approach mitigates the zonal effect and permits a more accurate estimate of commute length and subsequently a more reliable measure of wasteful commuting.

## **Contributions**

The value of this research can be identified in two following aspects—methodological improvements and substantive findings.

### Methodological improvements

- This research proposes a Monte Carlo simulation method to measure commuting length more accurately by first simulating individual resident workers and jobs that are consistent with their spatial distributions across the areal unit (e.g., census tract), respectively, and then simulating individual trips that are proportional to the existing area-based journey-to-work trip flows. It is a significant improvement over the zonal-level centroid-to-centroid approach, and can mitigate the aforementioned aggregation error and scale effect.
- Wasteful commuting, specifically the optimal commuting, is now reformulated as an integer programming approach targeted on individual trip makers rather than the traditional linear programming approach on the collective behaviors and patterns from the overall

commuters.

### Substantive findings

- This research recognizes that reporting errors from survey data and use of aggregated zonal data are two sources of bias in estimation of wasteful commuting that may cancel each other and thus conceal the problem. Specifically, the former tended to overstate the actual commuting length and led to overestimate wasteful commuting; and the latter (especially the use of large areal unit) gave rise to overestimated optimal commuting length and led to underestimate wasteful commuting.
- A relatively impressive explaining power by land use pattern (e.g., more than 90 percent by the job proximity index) is found in a medium-size city like Baton Rouge.
- This research reports the temporal trend of intraurban commuting pattern including the most recent period that is benefited from the newly-available 2006-2010 CTPP data.

### **Limitations and future work**

A major concern to this study refers to the ecological nature of the aggregated data. For example, the analysis in Chapter 6 investigates the relationship between commuting and wage rate; the above findings, however, are only suggestive but not necessarily applicable to individuals due to the limited aggregated data on wage (or income). More detailed individual data such as on wage or even other socioeconomic attributes could be employed in this research to help better understand commuting. This is especially feasible in the era of big data, data sources gathered from other human activities such as mobile phone call and social network may be adopted.

Second, this study does not consider neighboring parishes and hence the results might be limited. A future research could expand the study area by incorporating neighboring parishes to

see whether there are more pronounced changes in the metropolitan area and use high temporal resolution data to examine the impact of major external factors (e.g., significant fluctuation in gas price) on commuting. Also, more transportation modes such as public transit, bicycle, and walking could be incorporated to fully capture the urban mobility for all groups as not every socio-demographic group relies on auto for daily commute.

Furthermore, this study follows the line of existing research to measure wasteful commuting based on a simple assumption of equality of jobs and workers. As discussed previously, a future step could further relax this assumption by considering more constraints such as income, occupation, and household characteristics to make this topic more meaningful and practical.

As mentioned in the very beginning of this dissertation, understanding the temporal change of commuting and its underlying causes is a step toward the larger goals of traffic congestion mitigation and carbon emission control. A future step could concentrate more on planning and policy issues such as what policies may work well in reducing commuting or all-purpose trips in general. For example, we may simulate some plausible policy scenarios like flexible work schedules and telecommuting to see the impacts on trip reduction and ultimately on environment issues such as air pollution and global change.

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