ESSAYS ON CHOICE WITH SPATIAL HETEROGENEITY

by

JOSEPH F. WYER

A DISSERTATION

Presented to the Department of Economics
and the Graduate School of the University of Oregon
in partial fulfillment of the requirements
for the degree of
Doctor of Philosophy

June 2016

DISSERTATION APPROVAL PAGE

Student: Joseph F. Wyer

Title: Essays on Choice With Spatial Heterogeneity

This dissertation has been accepted and approved in partial fulfillment of the requirements for the Doctor of Philosophy degree in the Department of Economics by:

Wesley W. Wilson	Chair
Anne van den Nouweland	Core Member
Trudy A. Cameron	Core Member
Rebecca Lewis	Institutional Representative

and

Scott L. Pratt	Dean of the Graduate School

Original approval signatures are on file with the University of Oregon Graduate School.

Degree awarded June 2016

DISSERTATION ABSTRACT

Joseph F. Wyer

Doctor of Philosophy

Department of Economics

June 2016

Title: Essays on Choice With Spatial Heterogeneity

Consumers make choices based on an array of product attributes or consumer-specific characteristics. This dissertation includes three separate essays that examine consumer choice as a function of different consumer-specific characteristics. These attributes can be locations in a policy space or within an urban area, which drive transportation demand examined in the second and third essays.

In the first essay, I detail a model of United States presidential elections where voters' choices for president are proxied by electoral representatives. The aggregation of voter preferences at the state level results in rational candidates targeting the median voters of certain states. State-level campaign advertising has significant influence in voter decisions. I explore these two features in a model where candidates compete via spatial policy location and non-policy resource allocation. The resulting analysis demonstrates that the better-funded candidate always wins when pure strategy equilibria exist and that non-policy resource competition allows for divergence in policy platforms in equilibrium.

In the second essay, I examine transportation decision-making of commuters in Portland, OR. I examine transportation mode choices made simultaneously with the choice of whether to make multiple stops (termed travel complexity). I account for commuters' unobserved preferences for particular transportation modes. Using travel behavior data

collected by the Oregon Department of Transportation, I estimate the model using an error components logit (ECL) specification and find that not allowing for unobserved commuter preferences for particular transportation modes underestimates the value of travel time (VOT) and that, when making more complex trips, commuters who bicycle stick to bicycling.

In the third essay, I examine commuters' additional willingness to pay to avoid spending time in traffic congestion. Previous research has found that commuters are willing to pay 30-50% more to drive a minute less in congestion than to drive a minute less in free-flow traffic. Using an ECL specification, I find that when taking into account commuters' flexible work schedules, the estimated congestion premium rises to 80% that of free-flow VOT, but is 0% for commuters with flex-time. This implies that increasing the proportion of commuters with flexible work schedules will increase the number of peak-period drivers.

CURRICULUM VITAE

NAME OF AUTHOR: Joseph F. Wyer

GRADUATE AND UNDERGRADUATE SCHOOLS ATTENDED:

University of Oregon, Eugene, OR
Occidental College, Los Angeles, CA

DEGREES AWARDED:

Doctor of Philosophy, Economics, 2016, University of Oregon
Master of Science, Economics, 2012, University of Oregon
Bachelor of Arts, Economics and Diplomacy & World Affairs, 2010, Occidental College

AREAS OF SPECIAL INTEREST:

Industrial Organization and Applied Econometrics

PROFESSIONAL EXPERIENCE:

Graduate Teaching Fellow, University of Oregon, 5 years

GRANTS, AWARDS AND HONORS:

Kleinsorge Research Fellowship, University of Oregon, 2015

Kleinsorge Research Fellowship, University of Oregon, 2013

Omicron Delta Epsilon Honors Society, Occidental College, 2010

ACKNOWLEDGEMENTS

I would like to thank my committee for their assistance in the preparation of this manuscript; the department of Economics for the two Kleinsorge summer research grants that funded work on this project; John Voorheis for his helpful ado file, MQtime; and Becky Knudson at ODOT for facilitating my access to the data.

TABLE OF CONTENTS

LIST OF FIGURES

Figure Page

LIST OF TABLES

Table | Page

CHAPTER I

INTRODUCTION

Consumers make choices based on an array of product attributes or consumer-specific and/or product characteristics. This dissertation includes three separate essays that examine consumer choice as a function of different consumer-specific characteristics. A consumer's location is a major characteristic that drives his or her choice. This can be a location in a policy space, as in the first essay of this dissertation, or a location within an urban area, which drives transportation demand examined in the second and third essays. This dissertation has three substantive chapters. The first essay is a theoretical model that investigates the premise that voters are separated into different constituencies whose preferences vary over space and that candidate can target these constituencies with campaign resources. The second essay uses empirical techniques to investigate the joint choice of trip complexity and travel mode in urban transportation. The final essay separates the travel time of chosen transportation modes into congested and uncongested time to identify the disutility of congestion.

The first essay examines a topic in public choice—the strategic implications of the voting rule in the U.S. Presidential Elections. Voters in presidential elections in the United States do not, technically, vote directly for their preferred candidate. They are separated into their respectives states and then the vote of the majority of that state carries with it all of the *electors* from that state. The electors then vote for the president. Additionally, advertising and other non-policy resources at candidates' disposal have a significant effect on the candidate for which the voters in a state will vote. There is no work previous to this essay that allows for the candidates to compete strategically over both the spatial policy and non-policy components of voters' utility. This essay shows that pure strategy equilibria can be found where the better funded candidate always wins. However, for the investigated parameters, this is the case only when the better-funded candidate has significantly more resources than the lesser-funded candidate.

The second essay describes an empirical estimation of the joint choice of trip complexity and mode in urban transportation. When a commuter chooses to make a trip, there are two components to the trip: how many stops to make, and what mode to use (car, public transit, bike). Previous work in examining these decisions has allowed for the two choices to be made jointly, expanding the choice set and estimating via nested or mixed logit methods. I apply a cross-nested logit approach to estimate the joint choice. This allows for a richer error correlation structure that better captures correlation in the unobservable characteristics between choices of the same mode or the complexity. I find that a cross-nested logit model performs better in estimation than other logit models used in the previous literature. A cross-nested model also corrects for bias in the estimation of some effects of demographic characteristics on complexity and mode choice.

The third essay examines the additional disutility of time spent in traffic congestion (the "congestion premium") and how this premium changes if the commuter has a flexible work schedule. Previous research has found that commuters are willing to pay 50% more to drive a minute less in congestion than a minute less in free-flow traffic. In this paper, I permit the disutility of travel time in a discrete choice model to be separated into free-flow disutility and the disutility from driving in traffic congestion (the congestion premium). The data come from a detailed activities survey by the Oregon Department of Transportation (ODOT) and are augmented with door-to-door transportation mode travel times from online maps application programming interfaces (APIs). A wealth of commuter characteristics is included in these data, including whether the commuter has a flexible work schedules. Using an error components logit choice model of joint-choice in transportation mode and time of departure (TOD), I estimate the congestion premium in a revealed preference setting with door-to-door free-flow and congested travel time. I include a specification that allows for the congestion premium to vary according to whether the commuter has a flexible work schedule (flex-time). Before taking flex-time into account, the congestion premium is approximately 30% higher than that of free-flow travel time. This is similar to what has been found in previous studies. However, once the congestion premium is allowed to vary with flex-time, I find that commuters without flex-time have a congestion premium of approximately 80% while the congestion premium of those with flex-time is approximately 0% (meaning there is almost no additional disutility of driving in congestion). This effect implies that commuters with flex-time may be *more* likely to travel during peak hours as their disutility of being in congestion is much lower. If the magnitude of this effect is large enough, it will dominate these flex-time commuters' incentive to travel during offpeak times or take alternative modes. Indeed, the average marginal effect of flex-time on commuting during peak a.m. hours is 6.5% (early a.m. commuters substitute to peak a.m. with flex-time). Flex-time commuters are more likely to ride public transit or bicycle across all time, but also 3.5% more likely to drive during peak a.m. hours, suggesting that policies encouraging flex-time may have the unintended consequence of increasing traffic congestion.

CHAPTER II

A MODEL OF STRATEGIC ADVERTISING ALLOCATION AND SPATIAL VOTING IN U.S. PRESIDENTIAL ELECTIONS

Introduction

For presidential elections, the voting rule of the United States Electoral College is defined by a key institutional feature, namely that voters are divided amongst their respective states. Voters from each state are then aggregated and represented by the electoral votes allocated to their state. A primary effect of the voting rule is that competition for the presidency does not depend on the national distribution of voter preferences, but instead on the distribution of the median voters of the states. This influences the strategic choices of policy platforms and resource allocation of candidates competing to win the election. The contribution of this paper is to evaluate the strategic incentives that candidates face in an electoral-college voting rule where they may allocate non-policy resources (such as advertising or campaign stops) to specific states.

My model is built upon the spatial theory of voting. This theory is structured around the notion that policy alternatives and the preferences of voters can be communicated in a n-dimensional space. There exists strong empirical evidence that the decisions of voters over policy alternatives are, in fact, made in such a spatial setting.[1] The empirical literature is focused primarily on discerning the spatial preferences of individuals such as legislators or survey respondents.

Studies of the spatial preferences of legislators use psychometric techniques to estimate the relative placement of the legislators' optimal policy points within a policy

[1]Poole (2005) overviews estimation of spatial policy preference undertaken by him and his coauthors and explains the empirical techniques in detail.

space using yea-or-nay roll-call data. Poole and Rosenthal (1985) exploit how often legislators agree on a vote to find their relative placement in a policy preference space. Although one can imagine political policies taking shape in many dimensions, multiple empirical investigations of voting within legislatures have found that the vast majority of the variation in legislative voting in U.S. history can be accounted for using only one policy dimension.[2]

These psychometric techniques have also been applied to data from survey respondents to find the distribution of individual preferences nationwide, leading up to a presidential election. Schofield et al. (2011) integrate measures of spatial policy preferences of individuals and the policy positions of candidates in an empirical model of presidential elections. These authors find significant evidence that voters choose candidates based on a non-policy component, which the literature calls valence, in addition to policy preferences. The values of candidate-specific valence are found in the candidate-specific intercept of the logit estimation of voter microdata once the attribute-based spatial preference of the voters is taken into account. This finding supports a theoretical literature that posits that the divergence between the policies of candidates observed in the real world is attributable to the valence of each candidate.[3] In this paper, I investigate the incentives of the candidates to allocate non-policy resources (e.g., advertising and campaign visits). These non-policy resources can be viewed as influencing the candidate's valence in the state to which the resources have been allocated.

The theoretical and empirical research applying the spatial theory of voting to United States presidential elections has focused almost exclusively on the distribution of preferences within the popular vote. However, the outcome of a presidential election is

[2]The policy dimension found in empirical work on US legislatures appears to be simply "liberal-conservative."

[3]For theoretical discussions of valence see Groseclose (2001).

determined by the U.S. Electoral College rather than the popular vote. I show that the separation and aggregation in the U.S. Electoral College is relevant in that it incentivizes candidates to compete via state-specific non-policy resources such as advertising in addition to spatial policy location. This leaves a possibility that a better-funded candidate can have a decisive advantage. The model suggests that, in equilibrium, the better-funded candidate may have multiple policy positions she can adopt.

Details and History of the U.S. Electoral College

Every four years, in electing its president, the United States uses a voting rule that at best befuddles some of its voters and at worst disenfranchises many. Each voter casts a vote for one of any number of presidential candidates, but his vote does not necessarily garner that candidate any support toward the presidency. This vote is tallied and aggregated with all the votes in the state. Electors are then chosen who vote for the presidential candidate that the majority of voters within the state support.[4] The number of electors representing the voters of each state equals the number of representatives that state has in the House of Representatives plus two for its seats in the Senate.

Allotting a discrete number of representatives to every state in a "fair" manner based on the proportion of that state's population relative to the national population is not a trivial task.[5] Even when this is accomplished, the amount of influence that each state has in any simple voting game is by no means equal to the proportion of the total

[4]In many states, electors are not legally bound to vote for the candidate the majority supported, though they tend to follow this rule in practice. Additionally, Nebraska and Maine separate their total number of electors into one elector for each congressional district and two to represent the whole state. The democratic party primary in the U.S. uses a similar system (delegates and super-delegates proxying for voters), a recent close contest in the 2016 election has brought that system under close scrutiny in terms of "fairness" and its representation of voter preferences.

[5]See Young (1995) for a more detailed discussion on apportionment rules. The apportionment of congressional seats to states is a complex problem and the apportionment rule has undergone multiple changes since the country's inception.

votes that it possesses.[6] The allotment of votes and the relative influence states have in that allotment are two issues with the electoral college voting rule that have been investigated at length. In this paper, I investigate a third issue that has not typically been considered. I investigate the effect of the aggregation of preferences on the strategic incentives of candidates while they compete for electoral votes on a state-by-state basis and where candidates can target states by using non-policy resources.

To the best of my knowledge, the only work that has incorporated spatial preferences into a study of states' relative influence in the U.S. electoral college is Rabinowitz and MacDonald (1986). These authors make use of vote-share data from past presidential elections to map the preferences of state populations into a two-dimensional space and measure the relative voting power of the states given their positions in policy space and numbers of electoral votes. The method they use to measure voting power in a spatial context is equivalent to a numerical approximation of Owen's Modified Power Index (see Owen (2013)). Rabinowitz and MacDonald thus examine the effects of separation and aggregation in the context of spatial preferences, but they do not include an examination of its possible effects on the strategic incentives of candidates.

This separation and aggregation alone in the electoral-college voting rule can cause unequal influence amongst voters of different states. The electors vote for the majority's choice, so minority preferences within a given state will carry no weight in an election, even when the minority's choice is the same as the majority in another state. The latter state will be able to exert its relative influence towards this preference but the minority preference from the former state does not carry any weight. As a simple example, imagine that there are two states, a large state and a small state whose population ratio, and thus electoral vote ratio, is approximately 2:1, and two possible candidates, red and blue. In

[6] Early studies of voting power investigated the issue of states' relative influence at length. Owen (1975) uses multiple voting-power measures to compare the relative influence of states. For a detailed discussion on the properties and history of measures of voting power see Felsenthal and Machover (2005).

the large state, 51% of the voters prefer the red candidate and in the small state 65% support the blue candidate. The majority of the whole population supports the blue candidate, but the votes of the population are separated and aggregated in such a way by the electoral college that the red candidate would be elected. This example may be contrived, but in larger settings, the separation-and-aggregation problem does not disappear.[7]

The extremes to which the electoral college may distort the preferences of the total population can be seen in the 1860 and 1968 U.S. presidential elections. In 1860 Abraham Lincoln won the majority of electoral votes with less than forty percent of the popular vote. He received a plurality of the popular vote, as there were three competing candidates, but even if all the votes for his opponents had been cast for only one opposing candidate, the popular vote would have been distributed in such a way that Abraham Lincoln still would have won the majority of electoral votes (Sterling (1981)). This is a large-scale version of the two-state example of a minority victor discussed earlier, where small winning margins in large states would overwhelm large margins in smaller states. The 1968 presidential election saw the inclusion of a competitive third party candidate, George Wallace. As a result, the popular vote was distributed in such a way that, even though Richard Nixon received less than one percent more of the popular vote than Hubert Humphrey, Nixon gained 301 electoral votes to Humphrey's 191. These examples illustrate that the outcome of the electoral vote can be quite different from that of the popular vote. Candidates acting strategically would respond to the electoral vote, which is dictated by the preferences of the median voters of each state.

The disproportionate influence of voters caused by separation and aggregation is more pronounced when one considers its influence on the strategic decisions of candidates.

[7] Another issue is that, in this example, the smaller state in fact never has any influence as the larger state controls the majority of the electoral votes.

They compete for support from discrete blocks of voters rather than the majority of a single group. As mentioned earlier, candidates also compete along non-policy dimensions and this form of competition is different from the assumptions of the Median Voter Theorem.[8] Aside from positions taken in a policy space, candidates, in the real world, also compete using non-policy resources such as campaign time and advertising. Anecdotally, candidates spend much more time and money campaigning in "swing" states whose median voter preferences are located centrally.

Gordon and Hartmann (2013) investigate the amount of campaign advertising in each state in the 2008 presidential election. They find that the amount of advertising penetration in a state during a campaign rises sharply as the vote share approaches 50/50. Gordon and Hartmann also find that presidential campaign advertising has a statistically significant effect on voters' decisions. They instrument for the effect of advertising on vote shares within a county using the marginal cost of advertising in that market to control for the endogeneity of candidates' strategic allocation decisions.

The empirical insights of Schofield et al. (2011) and Gordon and Hartmann (2013) call for a model that builds a theoretical understanding of not simply the influence of preferences of individuals but those of groups of voters whose preferences are aggregated into voting blocks that candidates can target with non-policy resources like campaign advertising. A clear analysis of the strategic incentives of the candidates in the face of separation and aggregation can explain resource allocations by candidates (e.g., advertising spending) that have been observed in presidential elections. In this paper, I develop a model of policy location and non-policy resource allocation among states and identify the existence of pure strategy equilibria.

[8]The Median Voter Theorem is defined for a game with a group of voters whose policy preferences are distributed in a policy space and political candidates compete by choosing where to locate in that space. It is discussed in detail in Section 4 of this paper.

In the following sections, I work through the steps to construct a population aggregation model of spatial voting and non-policy resource allocation competition. First, I detail the basic utility maximization task faced by an individual voting deterministically. Second, I discuss the Median Voter Theorem and the influence it has had on research concerning electoral competition. Third, I discuss the implications of the institutional details of the United States Electoral College for the strategic decision-making of candidates. This is accomplished by constructing a model based on the knowledge that candidates may compete not only in terms of location decisions within a policy space, but also in terms of their allocation of a non-policy resource (such as advertising or campaign time, influencing state-specific valence) in an effort to influence voters. The analysis demonstrates, when candidate location decisions are unconstrained, that competition in terms of non-policy resource allocations has pure strategy Nash Equilibria when one candidate has a significant resource advantage. In these pure strategy Nash Equilibria, the candidates may locate away from the optimal policy preference of the median voter in the median state. Thus, non-policy resource competition permits divergence in policy platforms in equilibrium. I then compute an example illustrating the difficulty of analytically finding the boundaries that define the locations which the better-funded candidate can take in equilibrium.

Standard Model of Spatial Voting

Suppose there is a set of voters, I, who must vote for one of two candidates in an election. This is motivated by the fact that U.S. presidential elections, historically, rarely have competitive third-party candidates. Let $x_i \in \mathbb{R}$ represent the ideal policy point for voter $i \in I$ in a one-dimensional policy space. Let x_i be the bliss point for voter i. In each election, voters are presented with two candidates from which to choose. Each candidate is located at a particular point in the policy space. The utility function of voter i, casting a vote for candidate j, whose policy platform is z_j, can be described by $U_i(z_j) = f_i(z_j)$ where f is single-peaked at x_i and symmetric about x_i. For the rest of this paper, I will use $f_i(z_j) = -\beta(x_i - z_j)^2$ with $\beta > 0$.

Using cutting points allows for ease of analysis in empirical applications, as in Poole and Rosenthal (1985) and other empirical characterizations of spatial preferences, because this strategy reduces the description of the decision that the voters face to a comparison between the cutting point and the bliss point. Given the symmetry and single-peakedness of the utility function, all voters with bliss points to the left of the cutting point, in a given election, vote for the candidate located to the left of the cutting point and all voters with ideal points to the right of the cutting point vote for the candidate located to the right. This is a result of the symmetry of the utility function and the definition of C, (2.1), the cutting point of the election:

$$C = \frac{z_1 + z_2}{2}. \tag{2.1}$$

A graphical representation of candidate locations, the cutting point and voter bliss points can be seen in Figure 1.

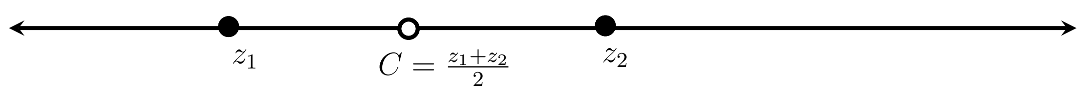


FIGURE 1. The Cutting Point

This standard spatial model of voting has been widely applied and has stimulated much theoretical and empirical work. I now move to a framework where candidates may choose their policy locations strategically. The following section describes the canonical model of electoral competition.

Median Voter Theorem

In the previous section, I described how an individual chooses the candidate they support in an election. I now consider a model with two candidates who choose their policy locations in an attempt to win the election. This is a foundational model in the public choice literature and closely resembles a Hotelling linear city model with no price competition.

Suppose that x is the vector of bliss points of the voters, $x = (x_1, x_2, ..., x_I)$. There are two candidates who each choose a location z_j from their policy space $\mathbb{R}$, where $j \in \{1, 2\}$. Throughout this paper, I assume that the only goal of the candidates is to win the election and that they have no policy motivations of their own. A candidate wins an election if they receive the support of the majority of the voters. If equal numbers of voters support each candidate, then either candidate wins with 50% probability. I define a set of players (the candidates), their strategies (locations in policy space), and their payoffs, namely winning the election or not (derived from voter decision making, the voting rule, and x). This constitutes a game, and thus the equilibrium strategy decisions of the candidates in this game can be analyzed.

Proposition 1 (Downs' Median Voter Theorem): Take a vector of the voters' optimal policy points x and two candidates who may locate anywhere in the policy space ($z_j \in \mathbb{R}$). A candidate wins when he or she garners more than half of the popular vote. The Nash Equilibrium of this game is such that both candidates are located at the median of x.

Proof: The proof is well known from previous work and closely resembles the reasoning for a Hotelling model in which firms locate to maximize market share in the absence of price competition. ■

Thus, when observing political contests where candidates are competing for support within one large population via policy location, the policy positions of the candidates become very similar and reflect the positions of moderate, centrist voters. Empirical evidence, such as Gordon and Hartmann (2013) and Huber and Arceneaux (2007), has demonstrated that the allocation of non-policy resources has a significant impact on voters' decisions. Next, I extend the model to reflect the separation-and-aggregation voting rule of the electoral college and allow candidates to allocate non-policy resources amongst the states.

Population Aggregation Model of Spatial Voting

The Median Voter Theorem detailed above is commonly discussed in the literatures on public choice, endogenous fiscal policy, and political science. However, its implicit assumption—that all voters have equal relative influence—is violated when applied to an election based on an electoral-college voting rule. An electoral-college voting rule is defined by voters being divided into multiple states and electors being chosen for each state to represent the majority opinion of their state. Thus, to model accurately an election using an electoral-college voting rule, one must take into account that the voters are separated and their preferences are then aggregated by majority rule within each state. We also want to consider, in addition to separation and aggregation, the fact that candidates target states with non-policy resources.

In the following population-aggregation spatial voting model, there is a set of voters, I, as before. In the previous section, these voters were all located within one nation and each one could contribute to their preferred candidate's vote share. The voting rule of the population-aggregation model of spatial voting (PAMSV) separates these voters into multiple states. Each state controls one electoral vote which is received by the candidate who garnered the support of the majority of the voters within that state.

Each state k, where $k = 1, 2, ..., K$ ($K \geq 3$), is home to a group of voters I_k. Every voter lives in one and only one state ($\bigcup_{k \in K} I_k = I$ and $\forall k, h \in K$ where $k \neq h$, $I_k \cap I_h = \emptyset$). Given voters i within each state and their bliss points x_i, let X_k be the vector of the bliss points of these voters within a state k.

Both candidates are endowed with a warchest, A_j, from which they must draw their non-policy resources.[9] Candidates simultaneously choose their policy location, $z_j \in \mathbb{R}$, and their non-policy resource allocation, $\lambda_j = \{\lambda_{j1}, \lambda_{j2}, ..., \lambda_{jK}\}$. The sum of all the resources they allocate cannot exceed their warchest; $\sum\limits_{k \in K} \lambda_{jk} \leq A_j$. Furthermore, candidate cannot assign a negative amount of non-policy resources to any state; $\lambda_{jk} \geq 0$.

In state k, given the location of the candidates in policy space and the resources λ_{1k} and λ_{2k} allocated to that state by the candidates, voters choose the candidate who maximizes their utility. A voter's utility from voting for a candidate is dependent on the candidate's location relative to the voter's bliss point and on the non-policy resources the candidate has allocated to that voter's state. The utility function of voter i, living in state k and choosing candidate j, is:[10]

$$u_{ijk} = -\beta(x_i - z_j)^2 + \lambda_{jk}$$

Once the candidates have chosen their policy positions and their allocations of non-policy resources, voters each cast their vote for the candidate who gives them the highest utility. The single electoral vote of the state goes to the candidate who earns the majority

[9] One can imagine a model where warchests are endogenously determined. If voters donate to presidential campaigns and are more likely to do so, or even donate more, when the candidate is located closer to the voters' preferred points in policy space, then warchests will be endogenously determined. If voter willingness to donate (e.g., as a function of income) is correlated with policy preference, then this could have a significant impact on the policy locations candidates choose.

[10] Models built upon the spatial theory of voting almost always use functional forms of utility that are single-peaks and symmetric about the ideal policy preference of each voter. There are other functional forms with the same properties that could be used with little impact on the intuition of the results.

of votes in that state. Let $y_{jk} = 1$ if k's electoral vote is cast for j and $y_{jk} = 0$ otherwise. Candidate j wins the election if she gains a majority of the electoral votes. Each candidate prefers winning the election to losing. Candidate j's payoff function is V_j:[11]

$$V_j = \begin{Bmatrix} 1 \text{ if } \sum\limits_{k \in K} y_{jk} > \frac{K}{2} \\ 0 \text{ if } \sum\limits_{k \in K} y_{jk} < \frac{K}{2} \end{Bmatrix}$$

As outlined earlier, the electoral vote of a state is assigned to a candidate if the majority of the voters in that state receive a higher utility from voting for that candidate than from voting for her opponent. To aid in determining which candidate the state's electoral vote supports, I let x_{mk} be the median voter of state k, $x_{mk} = \text{median}(X_k)$. The vector of median voters from all states is $X_m = (x_{m1}, x_{m2}, ..., x_{mK})$. Throughout this paper, I refer to the median voter in the median state as $x_m = \text{median}(X_m)$.

If the median voter in state k supports a candidate then, by the definition of the median, at least half of the remaining voters support the same candidate. Thus, if the median voter in state k supports a candidate then the candidate will receive k's electoral vote. Therefore, the vector X_m, the locations of the candidates, (z_1, z_2), and the vectors of non-policy allocations, (λ_1, λ_2), are sufficient to determine V_1 and V_2.

I have defined the population-aggregation model of spatial voting with large groups of voters in multiple states. However, the vector of bliss points of the median voters is sufficient to derive the payoffs. It is not the popular vote of the entire nation that determines the electoral vote, but the vector of median voters created by the separation and aggregation in the states. Candidates acting strategically will not respond to the distribution of bliss points at the national level, but only to the preferences of the median voters of the states. In the location dimension of the model, the policy location that

[11] The knife-edge cases for y_{jk} and V_j are ignored

candidates are incentivized to choose may not be the same as the location of the median of the nation (a result in contrast to the Median Voter Theorem).

I examine the model above for pure-strategy Nash equilibria in order to evaluate how candidates may behave when competing in an election with an electoral-college voting rule and non-policy resource allocation. The first case I examine is when the candidates have equal warchests, $A_1 = A_2$. I demonstrate that the population-aggregation model of spatial voting with equal warchests does not have a pure strategy Nash equilibrium. Next, I examine a case where the candidates do not have equal warchests and demonstrate that pure strategy Nash equilibria may exist. In these pure strategy Nash equilibria, the candidate with the larger warchest wins and the lesser-funded candidate does not have a large enough warchest to contest a majority of the states. However, as the lesser-funded candidate gains resources, the range of locations that the better-funded candidate may choose in equilibrium becomes more constrained.

PAMSV With Equal Warchests

I now examine the game for pure-strategy Nash equilibria when the candidates have equal warchests. The following proposition demonstrates that, in this case, a pure-strategy Nash equilibrium does not exist.

Proposition 2: A pure strategy Nash equilibrium does not exist in the PAMSV with equal war chests.

Proof: Let $(z_1, z_2, \lambda_1, \lambda_2)$ be a strategy profile. Suppose, without loss of generality, that candidate 1 is winning the election or is tied with candidate 2. $A_1 > 0$ and all λ_{1k} must be greater than or equal to zero. Therefore, there is at least one state, which I will denote as g, for which $\lambda_{1g} > 0$. Let ε be positive and between 0 and $\frac{1}{K-1}\lambda_{1g}$. Candidate 2 can deviate to $z_2' = z_1$ and $\lambda_2' = (\lambda_{11} + \varepsilon, \lambda_{12} + \varepsilon, ..., \lambda_{1g-1} + \varepsilon, \lambda_{1g} - (K-1)\varepsilon, \lambda_{1g+1} + \varepsilon, ..., \lambda_{1K} + \varepsilon)$. In the strategy profile $(z_1, z_2', \lambda_1, \lambda_2')$, candidate 2 is now winning. This can be seen as follows. $\lambda_{1g} - (K-1)\varepsilon > 0$ and thus is a valid allocation to state g. Also, λ'_2 is a valid resource allocation vector as $\sum_{k \in K} \lambda_{2k} = A_1 = A_2$. Because $z'_2 = z_1$ and $\lambda'_{2k} > \lambda_{1k}\ \forall k \neq g$, the median voters of K-1 states prefer candidate 2 to candidate 1. In state g, $u_{m1g}(z_1, \lambda_{1g}) = u_{m2g}(z_2, \lambda_{2g}) + (K-1)\varepsilon$, therefore candidate 1 earns g's single electoral vote. Thus, candidate 2 gets more electoral votes than candidate 1 in $(z_1, z'_2, \lambda_1, \lambda'_2)$ Consequently, $(z_1, z_2, \lambda_1, \lambda_2)$ is not a Nash equilibrium. ■

The PAMSV can be described as a stylized Colonel Blotto game with competition in spatial location.[12] As in a Colonel Blotto game where the players have equal resources, the PAMSV with equal warchests does not have a pure strategy Nash equilibrium. The location strategies of the candidates are unconstrained, and thus, a candidate who is losing in a given strategy profile is able to mimic the winning candidate's location strategy and reduce the competition to resource allocation only.

The lack of a pure strategy Nash equilibrium is related to the fact that, if candidates have chosen identical policy locations, once one candidate has allocated an arbitrarily small positive amount more to a state than her opponent, she wins the state. This is demonstrated in Figure 2. When candidate j has allocated nothing to state k and $\beta(x_{mk} - z_j)^2 - \beta(x_{mk} - z_{-j})^2 + \lambda_{-jk} > 0$ (thus candidate j does not have state k's vote), candidate j can increase λ_{jk} until there is a discontinuous jump in the number of votes that candidate j receives. The best reply correspondence thus fails to be upper-hemicontinuous, making it difficult for pure strategy Nash equilibria to exist.

PAMSV With Unequal War Chests

In the case of equal warchests, I have demonstrated that a pure strategy Nash equilibrium does not exist. I now investigate additional constraints or changes of parameters and what they may imply for the existence of equilibria and for predictions

[12]For an in-depth discussion and equilibrium analysis of the Colonel Blotto game, see Roberson (2006).

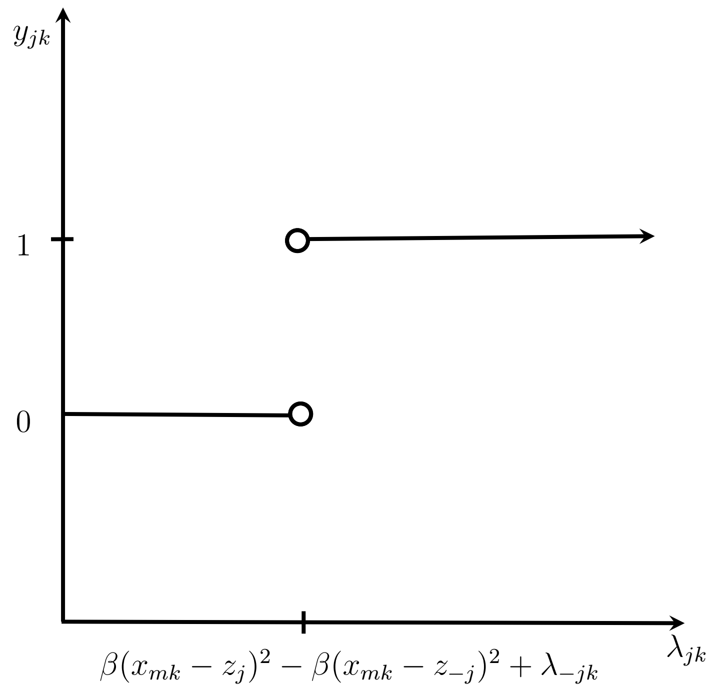


FIGURE 2. Votes earned by candidate j from state k

of play. An obvious step is to examine a case of the PAMSV where the candidates are not homogeneous in the sizes of their warchests.[13]

There is almost never an election where both candidates have the same amount of resources at their disposal. As before, the total resources available to a candidate constitute her "warchest." In contrast to the PAMSV with equal warchests, I demonstrate that equilibria exist for certain relative sizes of the players' warchests given the distribution of median voters.

It is important to point out what this equilibrium analysis demonstrates. Equilibria will exist in the cases where the parameters of the game (be it candidate resources, the number of states, or the preferences of the median voters) imply that the better-funded candidate wins the election.

[13]In this paper, I examine heterogeneity in warchests alone. However, other forms of heterogeneity and location constraints, which have been examined previously in the spatial voting literature (Calvert (1985) and Wittman (1990), for example), could also yield interesting results.

Proposition 3: If a strategy profile is a pure strategy equilibrium, then the lesser-funded candidate cannot win in that strategy profile.

Proof: Suppose there is a strategy profile $(z_1, z_2, \lambda_1, \lambda_2)$ where candidate 2 is winning. Candidate 1 can unilaterally deviate to $z_1' = z_2$ and allocate her resources such that $\lambda_{1k}' = \lambda_{2k} + \varepsilon, \forall k \in K$ for a small, positive epsilon. By assumption, $A_1 > A_2$, therefore $\sum_{k \in K}(\lambda_{2k} + \varepsilon) < A_1$. Thus, λ_1' is a feasible allocation for candidate 1. In the strategy profile $(z_1', z_2, \lambda_1', \lambda_2)$, candidate 1 is now winning all the electoral votes.

In every strategy profile where candidate 2 is winning, candidate 1 is able to deviate unilaterally and be better off. Therefore, no strategy profile where candidate 2 is winning can be a pure strategy equilibrium.■

In the following sections, without loss of generality, I maintain the assumption that $A_1 > A_2$ and examine how large that difference must be for equilibria to exist (ensuring candidate 1's victory). The constraint on the existence of equilibria is the total resources candidate 2 would need to win, given candidate 1's strategy. If candidate 2 has enough resources such that a location and an allocation exist where candidate 2 can win, then candidate 1's location and resource allocation cannot be part of an equilibrium.

For certain ranges of parameters there will be no unique equilibrium. Without the existence of a unique equilibrium, or even a countable number of equilibria, I am unable to make predictions concerning the strategies chosen by the candidates. There are multiple strategy profiles which result in the candidate with more resources winning and the candidate with fewer resources being unable to reposition and reallocate her resources in such a way as to change the outcome.

Suppose that candidate 1 is located at z_1, candidate 2 is located at z_2 and candidate 1 has allocated λ_{1k} non-policy resources to state k. If the median voter of state k is indifferent between candidate 1 or 2, the utility of the median voter, when voting for either candidate, must be equal. The following equality must hold:

$$\lambda_{2k} - \beta(x_{mk} - z_2)^2 = \lambda_{1k} - \beta(x_{mk} - z_1)^2 \tag{2.2}$$

Given this equality, candidate 2 can determine exactly how much of her non-policy resources she would need to allocate to state k in order to tie with her opponent, given both candidates' locations and the resources that her opponent has allocated.

$$\lambda_{2k} = \beta(x_{mk} - z_2)^2 - \beta(x_{mk} - z_1)^2 + \lambda_{1k}$$

Let $\Phi_k^2(z_1, z_2, \lambda_{1k})$ be the resource cost for candidate 2 to make the utility of the median voter of state k voting for her equal to that same voter's utility of voting for candidate 1. This value is a function of both candidates' locations and the resources candidate 1 has allocated to state k. $\Phi_k^2(z_1, z_2, \lambda_{1k})$ is defined to be always greater than or equal to zero because the amount of resources that candidate 2 may allocate to a state must be non-negative. If $\beta(x_{mk} - z_2)^2 - \beta(x_{mk} - z_1)^2 + \lambda_{1k} \leq 0$, then candidate 2 does not need to allocate any resources to win the state and thus $\Phi_k^2(z_1, z_2, \lambda_{1k}) = 0$.

$$\Phi_k^2(z_1, z_2, \lambda_{1k}) = \max\left\{\beta(x_{mk} - z_2)^2 - \beta(x_{mk} - z_1)^2 + \lambda_{1k}, 0\right\}$$

The sum of $\Phi_k^2(z_1, z_2, \lambda_{1k})$ over a winning subset of states yields the total value of the resources candidate 2 would need to expend in order to win. The definition of $\Phi_k^2(z_1, z_2, \lambda_{1k})$ assists in investigating how large the warchest of candidate 2's must be for candidate 2 to be able to compete in the election. The cost of winning state k for candidate 2, $\Phi_k^2(\cdot)$, is transferable across states as non-policy resources are fungible in this model.

The following proposition explains when a given location and allocation for candidate 1 may be a part of a pure strategy Nash equilibrium. When considering

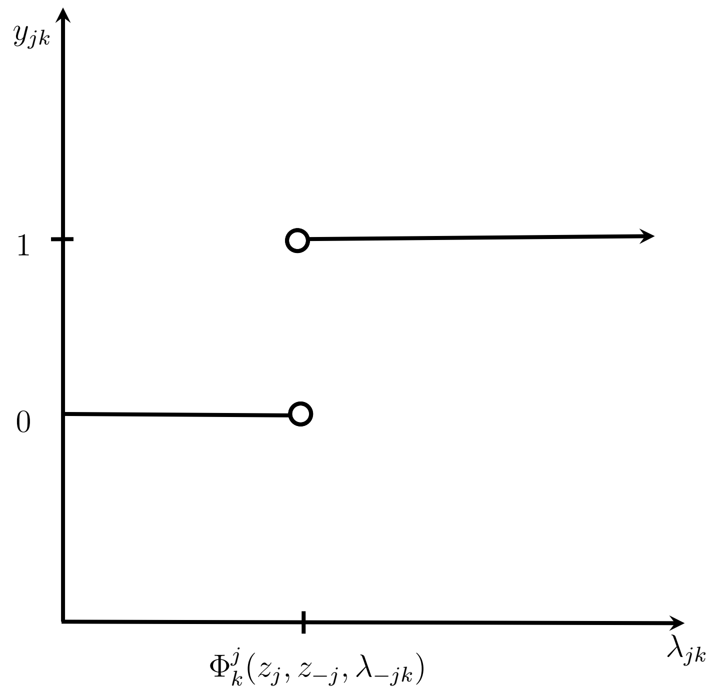


FIGURE 3. Resource cost of winning a vote

potential equilibria, it is important to consider sets of states that form a winning majority. Let W be the set of sets of states that form winning majorities.

Proposition 4: A strategy for candidate 1, (z_1, λ_1), can be part of a pure strategy equilibrium if and only if:

- (z_1, λ_1) are such that $\sum_{k \in \tilde{K}} \Phi_k^2(z_1, z_2, \lambda_{1k}) > A_2$, $\forall \tilde{K} \in W$ and $z_2 \in \mathbb{R}$

Proof From Proposition 3, we know that candidate 1 can mimic candidate 2's location and outspend candidate 2 in every state. Thus, in a pure strategy equilibrium, candidate 1 wins. If (z_1, λ_1) is a part of a pure strategy equilibrium, then candidate 2 has no combination of location and non-policy resource allocation available to her such that she can win. This implies that for all potential z_2, she does not have a large enough war chest to win a majority of the electoral votes. Therefore, if (z_1, λ_1) is a part of a pure strategy equilibrium, then $\sum_{k \in \tilde{K}} \Phi_k^2(z_1, z_2, \lambda_{1k}) > A_2$ holds for all z_2 and all majority subsets of states.

If $\sum_{k \in \tilde{K}} \Phi_k^2(z_1, z_2, \lambda_{1k}) > A_2$ holds, for a specific (z_1, λ_1) and all z_2 and $\tilde{K}$, then candidate 2 is unable to allocate her non-policy resources to gain more electoral votes than candidate 1. For (z_1, λ_1), there does not exist a (z_2, λ_2) such that candidate 2 can win. Therefore, if the constraint is satisfied for a specific (z_1, λ_1), then that strategy for candidate 1 is part of a pure strategy equilibrium. ■

In a situation where the lesser-funded candidate is locating rationally given her opponent's location, it stands to reason that the lesser-funded candidate has an incentive to locate in order to minimize the resources she needs to expend to win a majority. This reasoning gives insight into searching for equilibria given a general location and allocation of non-policy resources by the better-funded candidate. Such equilibria must satisfy a sufficient condition that candidate 2's warchest must not be large enough to win a majority when she has located in such a way as to minimize the resource cost of seizing a majority.[14] This ensures candidate 1's victory and constitutes an equilibrium.

Describing the Boundaries of Possible Policy Locations Taken in Equilibrium

Although candidate 1 always wins in a pure strategy Nash equilibrium, the resources at candidate 2's disposal place constraints on the strategies that candidate 1 can employ while still winning. It is a difficult task to find an analytical solution for the $z_1 \in \mathbb{R}$ that constitute the set potential pure strategy equilibria. As the position of a candidate moves away from a median voter, the cost of that median voter voting for the candidate in terms of non-policy resources rises non-linearly. The set of policy platforms that can be a part of pure strategy equilibria is also dependent on β, the number of states, and how large the warchests are in absolute terms.

[14] Although candidate 2 cannot win, her existance does put limits to the position that the better-funded candidate can take in equilibrium. One can imagine this being an important feature of an extension including primary elections and endogenous warchests as the existence of a contender in the primary can limit the better-funded candidate's policy positions she can take to guarantee victory.

One can simulate the space of potential equilibria given the model's parameters. However, these simulations are inconclusive as they only asymptotically approach a description of the boundary for equilibria and require much computational power to do so to a satisfactory degree. The simulations do, however, serve well in supplying intuition and identifying equilibria that lie outside of the boundary defined by attempted closed-form solutions.

In the current section, I give an example to illustrate the difficulty of describing analytically the boundary of equilibria given A_1 and A_2. Given β and the number of states, how much larger A_1 is than A_2 determines how far away from the median the better-funded candidate is able to locate. However, when pure strategy equilibria exist, the number of potential values of λ_1 for a given z_1 can be infinite (as the warchest is perfectly divisible). This feature, in addition to the discontinuous nature of the candidates' best reply correspondences, means that describing the potential values of λ_1 analytically may not be possible. The following example illustrates the case where there are five states, $\beta = 1$, and $A_1 = 10$. The distribution of median voters within the five states is $X_m = (-1, -.5, 0, .5, 1)$.

In an extreme case, where $A_1 = 10$ and $A_2 = 0$, candidate 1 can locate well to the left of -1 (the bliss point of the left-most median voter) and still win by resorting to a sufficient resource allocation. The reader may think that once candidate 1 can locate to the left of the left-most median voter in equilibrium that it becomes most effective for all her resources to be spent on the three left-most states only. If candidate 1 can hold on to the three left-most states, she can guarantee victory (three states is all that is required for a majority in this simple example). I will show that, even for this simple case, I can define a plausible candidate condition description of a boundary and show that this condition does not hold.

Candidate 1 simply must ensure that candidate 2 cannot win by locating at any of these three states' bliss points and allocating her whole warchest to that state. Thus, the following must be true for the three left-most states:

$$-\beta(x_{mk} - z_1)^2 + \lambda_{1k} \geq A_2$$

Rearranging and stating this condition for each of the three left-most states, given the median voter distribution and $\beta = 1$:

$$\lambda_{11} \geq A_2 + (-1 - z_1)^2$$

$$\lambda_{12} \geq A_2 + (-.5 - z_1)^2$$

$$\lambda_{13} \geq A_2 + (-z_1)^2$$

Candidate 1's warchest in this example is $A_1 = 10$. Therefore, the left-hand sides of these inequalities must sum to less than or equal to 10. Thus the sum of the right-hand sides must also be less than or equal to 10 for z_1 to be part of an equilibrium.

$$10 \geq 3A_2 + 3z_1^2 + 3z_1 + 1.25 \tag{2.3}$$

However, this relationship does not hold for all locations that can be supported in equilibrium. According to (2.3), once $A_2 > 2.9$ then the furthest candidate 1 may locate to the left and still have some allocation available that will guarantee victory is $z_1 \approx -.9$. This is now to the right of the left-most state. But a case can be found where a location still to the left of the left-most state can be supported in equilibrium when $A_2 = 3$. The resource allocation $\lambda_1^* = (1.14, 2.01, 2.75, 3.83, .27)$ is such a case (found via simulation).

The furthest left location of candidate 1 that can be supported by this allocation is $z_1 = -1.02$.[15]

The proposed allocation λ_1^* demonstrates that a candidate who has located beyond the left-most state cannot necessarily neglect to allocate resources to the right-most states in order to locate as far to the left as possible. Thus, the previously described intuition of locating to the left and being able to neglect allocating resources to the right-most states does not hold. Even in this very simple case, defining the boundary of equilibria analytically proves to be an elusive goal.

Conclusion

In this paper, I have presented the standard model of spatial voting and reviewed the intuition behind the Median Voter Theorem, a well-known result of a model where candidates compete for votes in terms of their spatial policy location. I show that separation and aggregation in the electoral college implies that candidates who choose optimal locations in policy space locate at the median voter of the pivotal state, which is not equivalent to the median voter of the national popular vote.

Building further upon the institutional knowledge and empirical work suggesting that non-policy resources such as advertising and campaign trips are relevant, I define a population-aggregation model of spatial voting where candidates can strategically allocate non-policy resources. My analysis shows that such a game has pure strategy equilibria, but only when one candidate has a significant resource advantage over the other candidate. The set of the locations that can be a part of these pure strategy equilibria appear to be diminishing as the lesser-funded candidate's warchest grows.

[15] This can be shown to be an equilibrium by evaluating using the sufficient conditions described in Proposition 4

I have investigated the strategic incentives and the existence of equilibria in a game where candidates may locate anywhere in a given policy space and allocate non-policy resources in any manner they see fit (subject to allocations being nonnegative and bound by the warchest constraint). As one would expect, there are additional constraints that could be placed on the candidates that may yield different results. Constraints on candidate locations, candidates who have policy motivations, or activist valence are examples of extensions that have been pursued in the existing spatial voting literature and appear to be natural next steps given that the PAMSV is, itself, an extension of that literature. Candidate preferences is a long-standing extension to the standard Downsian model, known as the Calvert-Wittman model, that has been examined and expanded upon significantly, see Wittman (1983).

The game in this paper is defined such that candidates choose their policy locations and their allocations of resources simultaneously. It could be argued that, in the real world, candidates stake out their policy positions early in the contest and then (over the course of the election season) allocate their resources competitively. Thus it might make sense to model the contest as a sequential game. I have investigated the sequentiality of the policy location and allocation decisions to some extent and have not found that it affects the incentives of the candidates, the outcome, or the economic interpretation of the model. However, this may not be the case when generalizations are made, so this issue remains an avenue for future research. Mixed strategy equilibria also remain an important avenue of inquiry as pure strategy equilbria are less likely to exist as the candidate's resources become closer.

Another maintained hypothesis behind the model in this paper is that the candidates are motivated by winning. Spatial voting models with more than two candidates, like those found in the literature, typically structure the payoffs such that candidates (or parties) maximize total votes as opposed to caring only about winning.[16] Allowing payoffs to be larger when the player earns more votes, even when they are losing, may be more appropriate in the case of parliamentary-style governments. This modeling feature is valuable in the multi-party setting because it partially explains why some parties locate on the fringes of policy space and cater to small groups of radical voters. This may be an extension of the PAMSV model that is worth exploring.

[16]See Schofield (2007) for a discussion of equilibrium in multi-candidate spatial voting games with valence.

CHAPTER III

URBAN TRANSPORTATION MODE CHOICE AND TRIP COMPLEXITY

Introduction

An understanding of the determinants of urban transportation mode choice is integral in urban policy because promoting alternatives to car-driving is a major means by which policy makers attempt to alleviate traffic congestion, diminish air pollution, and improve public health. Early studies have focused solely on mode choice. However, more-recent studies have combined mode choice with choices about the complexity of trips. Trip complexity refers to the notion that travelers can make multiple stops on a single trip. I examine the choice of the complexity of trips to work made jointly with the choice of three main urban transportation modes: driving a car, using public transit, and bicycling. Previous research in joint mode-and-complexity choice has centered on single nested logit models and mixed logit models that address correlation only in unobservables among options that share the same level of trip complexity. I find that a more-flexible error components logit (ECL) that addresses correlation in options with the same mode provides a better fit. I also find that my approach alleviates bias in the estimation of the value of travel time. Furthermore, I find that an increase in trip complexity due to higher income is associated with a shift from transit to car usage, but not with any significant change in bike usage.

Following most of the previous research, I define trip complexity as follows.[1] I define a trip as traveling from home to work and back. I make a distinction between a

[1] In some of the previous research on this topic of mode decisions and number of activities/stops, the entire round trip from home and back is called a tour or a trip chain while the movement from one stop to another is a trip. In this study I refer to the entire round trip as a trip and the intervening movements as trip segments.

single-stop “simple trip” and a multi-stop “complex trip”. A simple trip involves only one stop before returning home (e.g. to work). A complex trip involves more than one stop before returning home. A stop is defined as a new segment of a given trip with the purpose of consuming a different activity (e.g, picking up dry cleaning or stopping for coffee), rather than a mode change.[2] The main contributions of this paper include: (a.) my development of a ECL specification which allows for separate correlations in the unobservable characteristics of commuters in both mode and complexity choice, and (b.) examining bike usage in a mode-complexity setting.[3] The new ECL specification allows me to address correlations in unobservables among options that share the same mode as well as among options with the same level of complexity.

The literature on transportation mode choices is extensive and there have been many contributions but much work remains. In 2011, the year in which the data for this analysis were collected, commuters in urban areas with populations greater than three million faced an average annual travel delay caused by congestion of 52 hours. This is down from a peak of 65 hours in 2007, according to Schrank et al (2011). Congestion has been, and continues to be, a major issue throughout most major cities in the U.S. Since the economic downturn of 2008, growth in total vehicle miles traveled has slightly decreased, and growth in delay times has moderated somewhat. Nevertheless, congestion remains. In certain areas, it is a severe problem. The problem may grow worse as the U.S. continues to recover from the Great Recession and previously unemployed workers begin to use the roads at peak hours again and commuters with rising incomes are more likely to

[2] There is a range of different classifications of complexity within this literature. For example, Ye et al. (2007) rely exclusively on a binary complexity definition. Bowman and Ben-Akiva (2001) use a binary complexity definition but also include a separate choice of traveling in the middle of a work shift or returning home. Bhat (1997) is unique in directly modeling the number of stops made. Modeling the number of stops made directly can prove to be intractable as the number of commuters in the data choosing some alternatives (e.g. 5 stops riding transit) is very small.

[3] Bhat and Sardesai (2006) include non-motorized options but they take the complexity dimension of the trip as exogenous rather than endogenous.

choose complex trips and substitute away from public transit. However, I find that when commuters who choose to cycle make complex trips they do not substitute to a different mode. This provides evidence that policies to promote bicycle usage may be more resilient to changes in marcroeconomic conditions than those aimed at increasing public transit usage.

The demand for urban travel determines the number of cars on roadways. Given a fixed stock of roadway, usage of these roads beyond free-flow capacity creates congestion and lost time for commuters. Each additional commuter on the roads during peak hours contributes to the level of congestion that other commuters face, but these additional commuters do not internalize these costs in their own choices. Congestion is a classic example of an externality, the discussion of which has grown into a massive literature.[4] Through the use of congestion pricing, commuters could be forced to internalize, in a Pigouvian fashion, the external congestion costs they impose on others. However, aside from a handful of cases, congestion pricing policies have not been broadly implemented by policy-makers in the U.S.

The effectiveness of investment in public transit for mitigating congestion, in place of congestion pricing, is difficult to identify and, in some studies, has been found to be small relative to the high cost of public transit subsidies, as in Parry and Small (2009). However, recent research by Anderson (2014) identifies relatively large effects of public transit operation on congestion in Los Angeles (an approximately 47% decrease in congestion in the short-run). This large estimated effect is evidence that encouraging public transit usage among commuters can be effective in mitigating congestion and validates policy-makers' attempts to encourage commuters to choose public transit over cars. However, consumer travel decisions are simultaneously becoming more complex

[4]Recent contributions include Parry and Small (2009), Anderson (2014), and Proost and Dender (2008). Brueckner (2002) describes recent work that examines congestion and market power in the airline industry.

in that trips involve more stops. Greater trip complexity makes driving more attractive relative to public transit (Hensher and Reyes, 2000).

A rich array of discrete choice models has been applied to the problem of transportation mode choice in an effort to uncover demand parameters that can be used to predict the expected use of new modes and the anticipated effects of policy changes on the choice among existing modes. More recently, there has been an evolving literature on the complexity of trips.[5] In particular, commuters may travel directly to and from a single location or they may make one or more stops en route to their ultimate destination.

The relationship between trip complexity and mode choice has been investigated using many different stylized choice models. Bhat (1997) jointly estimates an ordered probit model for the number of stops in a trip, allowing the unobservables to be correlated with the unobservables of a multinomial logit model of mode choice. Bhat finds that ignoring the choice of complexity overstates the degree of substitutability between car and transit modes. Ye et al. (2007) also stand out for attempting to address the potential casual direction of complexity and mode choice by comparing bivariate probit and simultaneous logit specifications. Bivariate probit allows for two y variables to be modeled and for one of these to be conditioned on the value of the other, while simultaneous logit models permit both y variables to be conditioned on one another. The authors find that assuming the complexity choice is made prior to a mode choice in a bivariate probit setting leads to the best fit. Hensher and Reyes (2000) find, while comparing nested and mixed logit specifications of joint complexity and mode choice, that certain demographic characteristics are positively associated with commuters making more-complex trips and

[5] Some contributions in this literature include (in addition to ones cited in the following sections) Bhat and Koppelman (1999), Bhat and Singh (2000), Bowman and Ben-Akiva (2001), and Bhat and Sardesai (2006). Many of these studies more closely examine the type of complex trip (e.g. shopping on the way to work, versus dropping off children), for simplicity I focus purely on whether or not the trip is complex.

thus being less likely to use transit.[6] A mixed logit model with error components for alternatives that share both mode and complexity has not yet been applied in the mode-and-complexity choice setting (to the best of my knowledge).[7]

This more-general framework is useful in a joint-choice setting because each dimension has a choice-and-individual-specific unobservable component. This implies that joint-choice combinations that share a specific mode—such as "car", that is shared by "car-simple" and "car-complex"—are likely correlated in their unobservables and potentially violate the maintained iid error assumption that characterizes a conventional conditional logit model.

In this research, I use data collected from a survey of commuters in the City of Portland, Oregon, that focuses on commuters traveling to work. The fact that these are work trips implies a regularity in the mode decisions. However, Portland is also well known for its well-developed public transportation and bicycling infrastructure. Options often include buses, streetcars and light rail, making transit a relevant travel-mode option. There is also a strong representation of bicycling as a mode chosen for work trips. The data are extremely detailed and give considerable information about commuters' origins and destinations, the purposes of stops, and the socio-economic characteristics of these commuters. These data allow accurate calculation of travel time for each travel mode available to the commuter. Hence, an additional contribution of this research is an evaluation of the sensitivity of value of time (VOT) estimation to allowing more-flexible error structures in the joint-choice setting.

---

[6] This review of the mode-and-complexity literature is far from exhaustive but highlights the major papers most relevant to the present study.

[7] For an in-depth discussion about the development and application of mixed logit models, see Train (2009) Ch. 6. For a thorough exposition of the application and identification of error components mixed logit models, see Walker et al. (2007), Brownstone and Train (1998), and Revelt and Train (1998).

In the following section, I develop a mixed logit model of the joint mode and complexity choice with distinct error components for travel mode and trip complexity. In section 3, I describe the organization of the data and report descriptive statistics. I then estimate a mixed logit joint choice model that allows for correlation in unobservables between complexity alternatives as well as alternatives that are similar in mode choice. Estimation results are presented in section 4. I provide statistically significant evidence that a model with error components in both mode and complexity fits the data better than a more-restrictive model with error components only between complexities. Also, the complexity-only component model overestimates the choice to make complex trips in the face of changing demographics and underestimates VOT relative to the more-flexible mode-and-complexity components model. I then demonstrate that a uniform rise in incomes implies a fall in public transit usage in favor of car usage but that the cycling mode share remains unchanged.

Joint Mode-and-Complexity Choice Model

To address the possibility of simultaneous choices of both travel mode and trip complexity, I develop a model of joint choice with a error components logit (ECL) specification. The ECL specification relaxes the iid property of the joint-choice error terms and permits error components to be introduced by the researcher. A barrier to investigating the relationship between mode choice and complexity is the simultaneity of the choices that may bias the estimated effect of complexity on mode choice if complexity is modeled as being exogenous. For example, choosing to drive makes additional stops easier while, simultaneously, choosing to make additional stops makes driving a more attractive option.

I develop the mode-and-complexity decision as a three-way mode choice combined with a binary complexity choice of only one stop versus more than one stop. The choice of "primary" mode is limited to primarily driving, taking transit, or cycling. A primary mode is the mode that is used the most during a trip and is defined in detail in the data section. In the joint choice model, there are thus six options available to the commuter. The normalized utility for option j in a standard multinomial logit setting is:

$$U_{ij} = \alpha \text{ travel time}_k + \gamma \text{ price}_k + \beta_j' x_i + \varepsilon_{ij}$$

The systematic portion of utility is:

$$V_{ij} = \alpha \text{ travel time}_k + \gamma \text{ price}_k + \beta_j' x_i,$$

where j is a mode-and-complexity choice, $j \in C$, and k represents the mode in the mode-and-complexity choice. The disutility of travel time, α, and price, γ, are constant across modes. However, a mode-specific parameter vector, β_j, and observable characteristics of individuals, x_i, are multiplied. The additive unobservable characteristics, ε_{ij} are assumed to be independent and identically distributed Gumbel (i.e. type I extreme value). Thus the resulting expected probability of individual i choosing mode-and-complexity j is:

$$P_{ij} = \frac{e^{V_{ij}}}{\sum_{h \in C} e^{V_{ih}}}$$

The iid assumption for ε_{ij}, however, can be restrictive. As the estimation of the choice model is based on differences in scaled utility, the unobservable components are defined by observed differences in choice characteristics and preferences. If there is a common unobserved component shared by two or more options, then the usual maintained iid assumption will be violated. More-flexible error structures can be used, in this case, to allow for correlations among the unobservables. Factors that are unobservable but may impact the mode decision include: local congestion, the commuter's health conditions, the nature of the nearby built environment (i.e., neighborhood effects).[8] These are all examples of unobservables that may have a strong impact on the choice of car, transit or bike for a single individual, but are not recorded in these data. These unobservables are specific to modes but are shared across choices because there is a simple and a complex alternative for each mode alternative.[9] Given the very plausible existence of unobservables such as these examples, it is likely that the iid assumption is violated in this case.

The restrictiveness of the iid error structure in the choice model results in the independence of irrelevant alternatives (IIA) property for the associated choice probabilities. This issue is best described by the classic example of the "red bus, blue bus" problem. Suppose a commuter has three transportation modes available for a work trip: car, red bus, and blue bus. The red and blue buses are identical in every way except for one dimension (color) that is not relevant to the commuter's decision. The IIA property implies that if the red bus is removed, the odds ratios between the remaining options remain the same.[10] This forces formerly red-bus commuters to substitute to the blue bus in the same ratio as these options were chosen relative to red bus before it was removed. However, would one not expect this substitution pattern to be very different? If the red bus is eliminated then we would expect all red bus commuters to substitute to the blue bus because these modes are identical from the perspective of the commuter, where nothing else about the bus option changes except color.

[8]Observed data on the built environment and its effect on mode choice can be included. However, inclusion of neighborhood dummies would require at least doubling (quite possibly much more) the number of parameters to be estimated and significantly hinder separately identifying the parameters using these data. Also, gathering meaningful features of the built environment and including them in the data could prove to be overly burdensome considering the goal of this study, which is to examine the choice structure of mode-and-complexity choice as well as the apparent bias of neglecting mode-specific error components.

[9]Simple and complex trips are defined to be single-stop and multiple-stops respectively. Moving this cutoff (e.g., simple trips being 2 stops or less) did not change the qualitative results significantly. However, moving this window even further results in very few "complex" trips in the data as well as a diminished difference as more multi-stop trips become considered "simple".

[10]Assuming no change in seating, congestions, or arrival frequency of the remaining bus.

Making this intuition explicit in the model, suppose ε_{ij} is not iid. Suppose instead that ε_{ij} takes the form $\varepsilon_{ij} = \eta_{ik} + \tilde{\varepsilon}_{ij}$, where η_{ik} is an unobservable component specific to the commuter and a certain subset of the available alternatives, group k. Thus, η_{ik} allows the error term to take into account unobservables that are correlated across options within the group. In the context of the "red bus, blue bus" problem, one would allow for a "bus" group that includes both red and blue buses. This allows for a correlation in unobservables between bus options, making it more likely that the commuter will to stay within the bus group if they had previously chosen the red bus. Commuters who used to take the red bus before it was eliminated can be permitted to be relatively more likely to substitute toward the remaining blue bus. This is a similar argument to one that is made to motivate the use of a nested logit (NL) model. Error components for different groups of choices in an ECL can mimic the effects of the nests used in an NL model.

This correlation structure discussion also yields intuition for the researcher to use in making decisions about which types of error components to entertain. If the researcher is able to observe and include in the choice model all modal characteristics or preference heterogeneity that is correlated between modes, then this more-general error structure is unnecessary and a standard multinomial logit may be sufficient. Unfortunately, adequately capturing this heterogeneity is infeasible in most cases, so flexible error structures become necessary. Econometricians have increasingly modeled these group-specific error components with a random coefficient (or mixed) logit that employs error components.

A mixed logit specification that allows for random parameters will allow commuter i to have a utility for choosing option j of:

$$U_{ij} = \alpha_i \text{ travel time}_k + \gamma_i \text{ price}_k + \beta'_{ij} x_i + \varepsilon_{ij}, \tag{3.1}$$

where the distribution of α_i, γ_i, and β_i belongs to a parametric family imposed by the researcher. This is designated as the mixing distribution, f, the parameters of which, θ, are estimated (i.e., the mean and variance, if this assumed distribution is normal).[11] The choice probabilities can be expressed:

$$P_{ij} = \int \left(\frac{e^{V_{ij}(\beta)}}{\sum_h e^{V_{ih}(\beta)}} \right) f(\alpha, \gamma, \beta | \theta) d\beta \tag{3.2}$$

The utility of commuter i choosing option j can be modified to be consistent with an error components specification:[12]

$$U_{ij} = \alpha \text{ travel time}_k + \gamma \text{ price}_k + \beta' x_{ij} + \eta_i' z_{ij} + \varepsilon_{ij} \tag{3.3}$$

where η_i is a vector of error components, with zero mean and a variance to be estimated, and z_{ij} includes dummy variables that are equal to one if and only if the respective error component is included in the utility for option j. Error components in the mixed logit model are useful in that they allow for more-flexibile substitution patterns between the choices. However, the choice of how to specify these error components and random parameters requires researcher input, where a theoretical motivation is used to justify the correct specification. In this paper, I generalize from the one-level nested joint choice that has been frequently used and specify error components that approximate crossing nests. Each joint choice has a mode-specific error component as well as a complexity-specific error component.

Figure 4 illustrates which options for each individual include which error components. By including mode-specific components, I argue that there are common

[11]See Train (2009), Ch. 6, for discussion of different mixing distributions that have been used.

[12]Note that this specification does not rule out allowing for random β parameters. If the researcher wishes to mix over some coefficient then z_{ij} can simply be augmented to include the data related to that parameter. Furthermore, if $z_{ij} = x_{ij}$, then equation (4.3) is equivalent to equation (4.1).

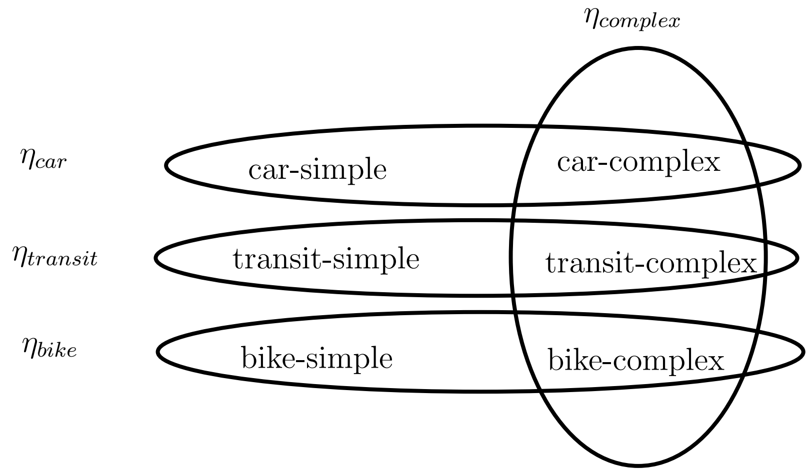


FIGURE 4. Error components shared between the six alternatives.

elements to the decision to choose, for example, both car-simple and car-complex that vary across individuals and are unobservable. Allowing for these unobservable commuter/alternative-specific common error components will allow for correlations within this subset of alternatives. Thus, as some observable attributes change, an individual who has chosen, for example, bike-complex is permitted to be more likely to substitute to bike-simple or another complex option, such as car-complex or transit-complex.

An error component is also included for all the complex alternatives but not included for the simple alternatives. This is a normalization that must be made if the estimates of the standard deviations of the error components are to be identified relative to an unidentified baseline category.[13] This is not a restriction of the model, but simply a normalization.

Another issue is that the choice probability of the mixed logit, equation (4.2), does not have a closed-form solution unless the mixing distribution, $f(\cdot)$, is degenerate. Thus,

[13]See Walker et al. (2007) for further discussion of identification in error components logit models. The specific issue of components covering two mutually exclusive subsets of the choice set is discussed in the work cited. An error components logit that approximates a nested logit with only two nests is not identified unless one of the components' variances is normalized to zero or both variances are restricted to be equal to each other. This is because the sum of the variances is identified but they are not identified separately.

to estimate the proposed error components specifications, I use maximum simulated likelihood (MSL) based on scrambled and shuffled modified latin hypercube sampling.[14]

Data

The data come from a survey fielded by the Oregon Department of Transportation (ODOT) in 2011. The survey includes a wealth of demographic information about each commuter and his or her household. Available variables include, for example, income, age, and educational attainment, as well as auto ownership. I use a subset of the data that pertains to the Portland metropolitan area (including Vancouver, WA).

The mode choice assigned for a given work trip is identified using detailed trip-segment information. The data include information on how far the commuter traveled for each segment of her trip and what mode she used on that segment. A "primary mode" interpretation of mode choice is used in this study in order to make transparent and explicit my strategy of reducing multimodal trips to a single primary mode. I calculate the share of total distance traveled for which a commuter used a specific mode and apply a decision rule. Each mode-share calculation has a highly bimodal distribution with the most common shares being at each of the extremes: 0 and 1. Histograms of the mode share for trips where mode shares are not strictly equal to 0 or 1 are shown in Figure 5. The data shown in Fugre 5 are restricted to shares not equal to 0 or 1 so that the distribution within that interval can be viewed more easily. The vertical lines in Figure 5 are my discretionary "primary mode" cutoffs used for the models presented in this paper. If the share of a mode in a given trip is above the cutoff that mode is designated as the primary mode.

[14] Scrambled and shuffled modified latin hypercube sampling has been shown to perform better than scrambled and shuffled Halton sequences, as shown by Hess et al. (2006). For a discussion of MSL estimation of mixed logit models see Train (2009), Ch. 6.

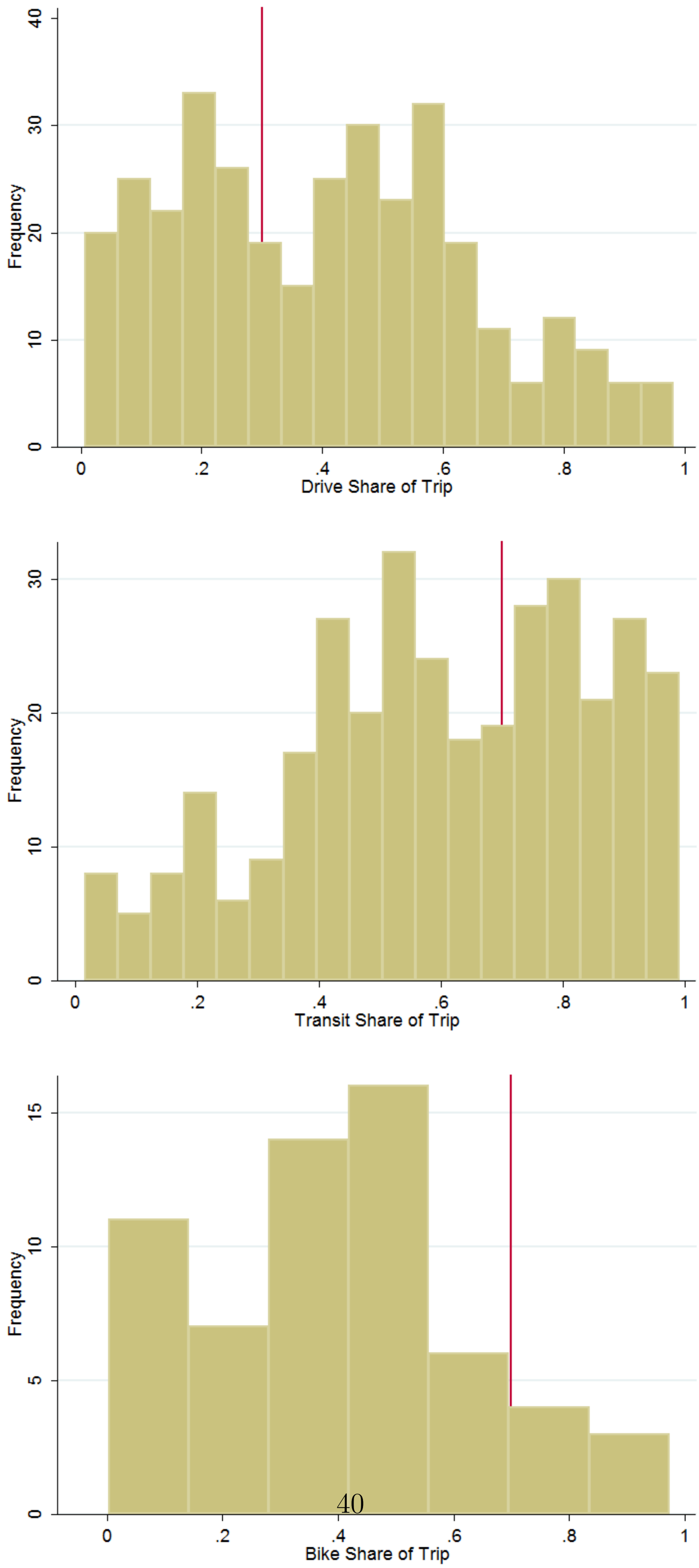


FIGURE 5. Distance-Traveled Share of Trip, by Mode

I apply a decision rule based on natural breaks found in the shares of total distance by a particular mode for a given trip. If over 70% of the distance traveled on the trip was via bike, then bike is determined to be the primary mode used. If over 30% of the distance traveled on the trip was via car, then car is determined the primary mode used. If over 70% of the distance traveled on the trip was via transit then transit was designated as the primary mode used.[15]

The ODOT survey also includes extremely detailed spatial origin-destination data. I use the spatial coordinates of home and work locations to compute travel times and distances traveled for alternate modes.[16] The price of driving is approximated by multiplying the distance traveled in miles while driving by $0.585/mile, (AAA, 2011), and also adding the approximate daily cost of parking in downtown Portland if the cost of parking (approx. $7/workday) is not provided by the commuter's employer. The price of cycling is approximated by multiplying the distance traveled while cycling by $0.10/mile, Litman (2013). The price of transit in Portland is $2.50 for a one way trip, or $0 if the commuter's employer provides a free transit pass.

Table 1 contains the marginal summary statistics for commuter and mode characteristics by mode chosen. In this sample, over 8% of commuters report bicycling as their primary mode to work. This is high compared to the rest of the United States as Portland has invested significantly (in advocacy and infrastructure) to encourage bicycle

[15] As some trips have mode shares that are relatively evenly balanced between two modes one may wonder how changes in the cutoffs influence the results presented in this study. I have conducted a sensitivity analysis across a variety of of cutoffs shifted from those presented here and found little change in the results.

[16] The coordinate data is processed using a Stata ado function, Voorheis (2015). This function takes advantage of the publicly available online resources of Open Street Maps (OSM) and Mapquest through an API request. Using the ado, the researcher specifies which variables contain the origin and destination data and the mode for which to calculate the travel time between these two points. The API can return the travel time and distance traveled for the modes driving, public transit and cycling. This allows an alternative-specific measure of travel time to be included for all the mode alternatives that were available to the commuter.

transportation. Some notable regularities in the data include that car drivers tend to be older, while transit and bike users' average ages are progressively lower. College education appears to be significantly higher for transit and bicycle users. This relationship does not seem to hold when ECLs are estimated, as college education becomes a significant predictor of choosing to cycle. Commuters who choose to bike tend, on average, to have a shorter bicycle time than transit time to work. This suggests that commuters may respond to an incentive to cycle if they can "beat the bus" to work.

Table 2 reports choice of primary mode across different income groups. It appears that those at the very bottom of the income distribution are much more likely to cycle to work than are those in the next income category. However, within income groups bicycling maintains its relative share (after this initial decline) in the face of further income increases. The likelihood of choosing a car mode appears to be steadily increasing with income. The propensity to use transit falls monotonically as income is greater.

These descriptive statistics suggest that for the lowest income group, cycling is used more in lieu of paying for public transit. Then, as income rises, lower-income consumers immediately substitute away from cycling to driving. However, once that initial change has happened, as income increases further, commuters begin to substitute from transit to driving while the proportion of commuters using bike as their primary mode stays relatively stable. This points to a potential for complexity not to pose a significant barrier to cycling. Intuitively, there is no wait time when you wish to back on your bicycle, but extra wait time for transit for each stop you make. Any patterns in these marginal descriptive statistics, however, are not *ceteris paribus* (and may reflect correlated differences in other demographic characteristics or unobservables as well). Nevertheless, it can be enlightening to investigate simple marginal descriptive statistics before applying more-complex models, to see whether these marginal patterns change as additional controls are introduced into the models.

TABLE 1. Summary Statistics of Commuters by Mode Chosen

	Drive	Transit	Bike
Percent Primary Mode	82.59%	9.02%	8.39%
	Mean	Mean	Mean
Modes	(S.D.)	(S.D.)	(S.D.)
Age	44.06	42.45	39.76
	(12.87)	(13.88)	(11.87)
College degree	0.713	0.743	0.737
	(0.452)	(0.437)	(0.440)
Household Income (in $1000s)	80.33	56.30	69.06
	(41.48)	(37.87)	(42.42)
Male	0.494	0.493	0.625
	(0.500)	(0.500)	(0.484)
Household size	2.801	2.134	2.619
	(1.342)	(1.205)	(1.127)
Household Vehicles per person	1.073	.578	.676
	(0.482)	(0.550)	(0.395)
Employer provided free parking	0.831	0.438	0.688
	(0.374)	(0.497)	(0.463)
Employer provided transit pass	0.089	0.222	0.171
	(0.285)	(0.416)	(0.377)
Driving travel time (minutes)	18.59	19.12	14.05
	(12.68)	(9.26)	(8.62)
Transit travel time (minutes)	67.31	52.92	46.17
	(40.18)	(22.96)	(27.26)
Bicycling travel time (minutes)	54.71	51.54	33.06
	(53.96)	(34.24)	(28.78)
Price of driving	6.552	8.753	5.267
	(6.046)	(4.569)	(4.280)
Price of transit	2.275	1.94	2.071
	(0.714)	(1.04)	(0.943)
Price of bicycling	0.939	0.848	0.546
	(0.956)	(0.557)	(0.471)

TABLE 2. Mode Choice by Household Income

	Income Under $35k	$35k-$50k	$50k-$75k	$75k-$100k	$100k-$150k	Over $150k
Modes	Share	Share	Share	Share	Share	Share
Drive	71.2%	79.6%	83.2%	88.0%	87.4%	91.8%
Transit	17.0%	13.4%	9.0%	5.0%	4.9%	3.3%
Bike	11.7%	6.9%	7.7%	6.9%	7.6%	4.7%
Observations	383	359	791	809	879	455

TABLE 3. Frequency of Trip Complexities

Number of Segments	Percent of Sample
1	48.67%
2	19.91%
3	14.40%
4	7.81%
≥5	9.24%

As discussed in the model section, mode choice has a strong connection to trip complexity. The demand for complex trips influences the propensity to choose certain modes. From an intuitive perspective, this is because certain modes have more flexibility and the utility from choosing more-flexible modes increases as complexity increases. Table 3 contains the frequency of trip complexities observed in the data. Complexity is measured as number of segments in a trip, not counting stops made solely for the purpose of changing modes. For example, if a commuter departs from home in a car, parks at a park-and-ride to access transit, stops at a coffee shop along the way and then walks to her office, the trip will still have only two segments. The first segment was from home to the coffee shop and the second from the coffee shop to work. A mode change alone does not define a separate trip segment. A segment of a trip is defined as between two activities (e.g., work, shop, or eat).

When viewing a cross-tabulation of mode and complexity, one can see that mode choice is closely tied to the complexity of the trip the commuter is planning to make.

TABLE 4. Share of Mode by Trip Complexity

Number of Segments	Drive	Transit	Bike
1	77.7%	11.0%	11.1%
2	85.3%	9.1%	5.5%
3	85.3%	7.9%	6.7%
4	88.6%	4.5%	6.80%
$\geq$5	92.7%	3.5%	3.7%

Driving alone in an automobile is very flexible and allows one to move quickly from location to location at the driver's convenience. Cycling is very similar, since a bicycle is also an independent vehicle. However, it is much more difficult to travel long distances on a bicycle. Transit usage is the most at odds with complex trips as transit is only feasible for fixed routes and at set times. Table 4 demonstrates this intuition. For very simple trips of one segment (i.e., going straight to work), the proportion of transit and bicycle users is relatively high. However, once the trips become more complex than just one segment, transit and bike usage drop significantly. For each additional segment beyond three, transit usage drops by almost half. The proportion of trips whose primary mode is bike appears to be resilient to increases in complexity after the initial drop (i.e. after moving from one segment to two) and continues to fall to approximately the same share as transit at ≥ 5 segments.

Next, I consider descriptive statistics for the joint mode-and-complexity choice. Table 5 contains the absolute frequency of each of the six joint choice possibilities made within the sample. Car is the only mode for which complex trips are more common than simple trips. This is not the case for transit and biking. Table 5 also contains summary statistics for commuters separated by their joint mode-and-complexity choices. The bike-simple option has a uniquely high proportion of males.[17] Household income

[17]Household structure could be a significant factor to this higher propensity of cyclists to be male. The differential impact of males being single or married and having children or no children would be an interested avenue of inquiry.

TABLE 5. Summary Statistics of Commuters by Mode-Complexity Chosen

	Car-Simple	Transit-Simple	Bike-Simple	Car-Complex	Transit-Complex	Bike-Complex
SHARES	37.83%	5.38%	5.44%	44.77%	3.64%	2.95%
VARIABLES	Mean	Mean	Mean	Mean	Mean	Mean
	(S.D.)	(S.D.)	(S.D.)	(S.D.)	(S.D.)	(S.D.)
Age	43.76	41.68	39.55	44.32	43.59	40.13
	(13.18)	(13.96)	(12.05)	(12.11)	(13.74)	(11.56)
College degree	0.643	0.722	0.715	0.772	0.775	0.777
	(0.479)	(0.449)	(0.452)	(0.419)	(0.418)	(0.418)
Household Income ($1000/yr)	75.58	53.02	67.96	84.38	61.33	71.32
	(39.94)	(37.98)	(39.42)	(42.33)	(37.30)	(48.22)
Male	0.525	0.491	0.683	0.469	0.495	0.517
	(0.499)	(0.501)	(0.466)	(0.499)	(0.501)	(0.502)
Household size	2.72	2.08	2.64	2.86	2.21	2.56
	(1.331)	(1.119)	(1.150)	(1.349)	(1.323)	(1.08)
Household vehicles per person	1.06	0.627	0.714	1.07	0.506	0.608
	(0.486)	(0.610)	(0.400)	(0.479)	(0.439)	(0.379)
Employer provided free parking	0.855	0.432	0.715	0.811	0.449	0.638
	(0.352)	(0.496)	(0.452)	(0.391)	(0.499)	(0.482)
Employer provided transit pass	0.087	0.245	0.195	0.091	0.189	0.126
	(0.283)	(0.431)	(0.397)	(0.287)	(0.393)	(0.333)

appears to be quite high for car users who make complex trips as well as for both simple-trip and complex-trip bike-riders. College education (including associate degrees and technical degrees) seems to be positively associated with complexity for users of all modes. Employer-provided free parking, unsurprisingly, appears to be associated with car mode choice. While those who take transit are far less likely than car drivers to have employer-provided free parking, this is less the case for commuters who choose to bike to work.

Results

Model Estimation

Three alternative ECL model specifications are estimated. All three allow for unobserved heterogeneity in the value of travel time (VOT) by permitting each commuter's travel time disutility parameter to be drawn from a distribution, the mean and variance of which are estimated. These specifications include: only a complex-trip error component, three mode-specific error components, and a crossing-components specification having both complex-trip and mode-specific error components. The crossing complexity-and-mode components is the preferred specification as it is the most general and provides the best fit. The mixing distribution chosen for the coefficient on travel time is the lognormal distribution. A lognormal mixing distribution constrains the random parameter being estimated (in this case, the normalized utility of one minute less in travel time) to be strictly positive. This assumes, all else equal, that commuters always prefer to spend less time traveling. All three models include demographic controls to allow for heterogeneity in preferences as well as alternative-specific constants.[18]

Table 6 contains selected parameters of interest estimated from three specifications: a complexity-components model, a mode-components model, and a crossing-components model. In all three cases, the estimated marginal disutilities of travel time and price are used to derive VOT.[19] The complexity-component (in both the simple complexity-component and the crossing-components models) is significantly different from zero. The bicycle error component in both the simple mode-components and crossing-components models is also significantly different from zero.

In the last two models in Table 6, the estimated variances of the car-mode and transit-mode error components are not significantly different from zero. This implies that there is very little unobserved heterogeneity in preferences for these modes. This is most certainly not the case when employer-provided parking and free transit passes are omitted from the construction of the price variable. If the price effects of these employer transportation policies are not included in the data, then the transit mode

[18]The parameter estimates for the demographic controls and alternative-specific constants for each specification are contained in Appendix Tables A.1, A.2, and A.3

[19]VOT is calculated by examining the compensating price decrease needed to completely offset the utility loss from an increase in travel time. For the specifications estimated in this study: $VOT = -\frac{\exp(\hat{\alpha}+\hat{\sigma_\alpha}^2/2)}{\hat{\gamma}} * 60\text{minutes}$.

error component becomes very large and significant. Also, model performance declines significantly and VOT estimation becomes less precise.

The VOT estimates contained in Table 6 appear to be sensitive to the assumed form of the error components structure. Note the difference in VOT estimates between the complexity-component and mode-components models. The mode-components model estimates VOT at $5.81 per hour higher than in the previous model (approximately a 28% increase). Mode and travel time are correlated, however, so failure to account for unobserved heterogeneity in the utility of using specific modes biases downward the estimate of VOT. The source of this bias comes specifically from failing to account for unobservable heterogeneity in the preference for bicycling. Travel time tends to be greater, and prices lower, for the bicycling mode option compared to other modes. Consequently, failing to account for unobserved heterogeneity appears to bias the coefficient on travel time downwards (more negative) and the coefficient on price upwards (less negative). Finally, reinstating the complexity error component causes the estimate of VOT to decrease, but the difference between the crossing-components and complexity-component models still points toward an underestimate of VOT by the complexity-component-only model. This is most likely caused by the correlation between complex trips and the car mode, which tends to have the lowest travel time. The difference in VOT between the complexity-components and the crossing-components models is $3.42/hr (approximately a 14% increase).

In the crossing-components model, both the complexity error components and bicycle error components are statistically significantly different from zero. Also, a likelihood ratio test comparing the mode-components-only and the more-general crossing-components models rejects the restrictions embodied in the mode-components model (at the 1% level). A likelihood ratio test comparing the complexity-component-only and the more-general crossing-components model also rejects the complexity components model (at

TABLE 6. Mixed Logit Model Estimation with Error Components

	Complexity-Component Model	Mode-Components Model	Crossing-Components Model
Parameters	Estimate	Estimate	Estimate
	(S.E.)	(S.E.)	(S.E.)
Travel Time (α)	-2.675***	-2.029***	-2.119***
	(0.121)	(0.239)	(0.195)
Travel Time (S.D. α)	0.727***	0.837***	0.795***
	(0.092)	(0.079)	(0.085)
Price (γ)	-0.224***	-0.375***	-0.360***
	(0.021)	(0.071)	(0.055)
Complex (S.D. η_{complex})	4.808*		5.375*
	(3.462)		(3.613)
Drive (S.D. η_{drive})		0.252	0.257
		(0.521)	(0.532)
Transit (S.D. η_{transit})		0.432	0.194
		(0.705)	(0.911)
Bike (S.D. η_{bike})		4.243***	3.694***
		(1.313)	(1.033)
Mean VOT (derived)	$24.04/hr***	$29.85/hr***	$27.46/hr***
	(3.150)	(3.915)	(3.257)
Log-Likelihood	-3885.21	-3881.51	-3877.99

N=3676

*** p<0.01, ** p<0.05, * p<0.1

Note: Demographic characteristics and alternative specific constants are included in the models specified, see Table 7 for average marginal effects implied by cross components model estimates. For parameter estimates of demographic characteristics see Table A.1, A.2, and A.3. Value of travel time (VOT) when the coefficients on travel time are lognormally distributed is: $VOT = -\frac{\exp(\hat{\alpha}+\hat{\sigma_\alpha}^2/2)}{\hat{\gamma}} * 60\text{minutes}$. VOT standard errors are bootstrapped.

the 1% level). This suggests the more-flexible substitution patterns across both dimensions of the choice set (mode and complexity) are important to model the decision process accurately.

Interpretation and Application

Table 7 reports the average marginal effects of price, travel time, and demographic controls in the crossing-components model. Average marginal effects examine the change in the fitted probability of choosing each option, averaged across all the observations in the data. They are more easily interpreted than are individual parameter values. The marginal effect of income is negative for all simple options and positive and large for the car-complex option. The marginal effect of income on bike-complex is positive and offsets the negative effect of income on bike-simple. Mode-specific price and travel-time marginal effects all have the expected signs. The marginal effect of an increase in the price of driving on the probability of choosing to drive is significantly larger than the own-price marginal effects for other modes. Similar results obtain for the other own-mode travel time marginal effects estimates.

Discrete marginal effects are estimated for the influence of gender and college education on mode-complexity choice.[20] Having a terminal college degree is significantly associated with choosing car-complex, transit-complex, and bike-simple relative to other options. However, the effect of gender on the probability of choosing car-complex is much larger than the its effect on other options. Males are significantly more likely to choose simple trips for any modes compared to females. Males are also significantly more likely to choose bike-simple and significantly less likely to choose car-complex compared to females. This may reflect typical gender differentiation in household responsibilities such as grocery-shopping or childcare drop-off and pickup.

Plots of the average probability of choosing complex options or specific modes are included in Figures 7 and 8. These plots compare the average predicted probability of complexity or mode, across the observed range of the variables in the data for the complexity-component and crossing-components models. Figure 6 gives average probability plots of mode choice across age and income (mode-specific probabilities are calculated by summing the probability of mode-simple and mode-complex). Higher income

[20]When the marginal effects of dummy demographic characteristics are evaluated the predicted average probability of choosing each option is compared between two artificial datasets. These artificial datasets are identical to the estimation dataset except that in first the dummy demographic variable for all individuals is set to 1 and in the other set to 0. The change in the discrete variable is assumed to be uncorrelated with any other explanatory variables. This is done in lieu of estimating an instantaneous marginal effect as is done for continuous variables (e.g. price and travel time). Examining the difference in choice probabilities based on a discrete change in a discrete variable is preferable to approximating the slope at the mean of a discrete variable (e.g., the instantaneous marginal effect of being male).

TABLE 7. Crossing-Components Model, Average Marginal Effects (in % points)

	car-simple (base)	transit-simple	bike-simple	car-complex	transit-complex	bike-complex
VARIABLE	Marginal Effect (S.E.)	Marginal Effect (S.E.)	Marginal Effect (S.E.)	Marginal Effect (S.E.)	Marginal Effect (S.E.)	Marginal Effect (S.E.)
Instantaneous Marginal Effect						
Age (and Age^2)	-.155**	.062*	-0.018	.067	.101***	-.057***
	(.0668)	(.0450)	(.0294)	(.0630)	(.0141)	(.0171)
Household Income ($1000/yr)	-.027**	-.049***	-.011*	.096***	-.024**	.016***
	(.0137)	(.0112)	(.0074)	(.0165)	(.0120)	(.0005)
Travel Time Drive	-.363***	.173***	.204***	-.287***	.169***	.103***
	(.0219)	(.0335)	(.0228)	(.0267)	(.0120)	(.0148)
Travel Time Transit	.178***	-.209***	.040***	.164***	-.197***	.024***
	(.0178)	(.0296)	(.0076)	(.0253)	(.0115)	(.0034)
Travel Time Bike	.185***	.036***	-.245***	.122***	.028***	-.127***
	(.0274)	(.0076)	(.0287)	(.0164)	(.0037)	(.0175)
Price Drive	-1.278***	.727***	.585***	-1.037***	.717***	.284***
	(.0089)	(.1471)	(.0700)	(.1014)	(.0528)	(.0478)
Price Transit	.750***	-.898***	.188***	.695***	-.847***	.111***
	(.0808)	(.1293)	(.0298)	(.1048)	(.0519)	(.0157)
Price Bike	.528***	.170***	-.774***	.341***	.129***	-.395***
	(.0839)	(.0313)	(.0979)	(.0487)	(.0155)	(.0626)
Discrete Marginal Effect						
College degree	-11.377***	.691	1.522*	7.200***	2.429***	-.466
	(1.9151)	(.5875)	(1.0249)	(1.6105)	(.4392)	(.5959)
Male	1.492	1.152***	4.357***	-6.711***	-0.623*	.333
	(1.7724)	(.4572)	(.5097)	(1.4695)	(.4201)	(.3617)

N=3676
*** p<0.01, ** p<0.05, * p<0.1
Note: Standard errors are bootstrapped.

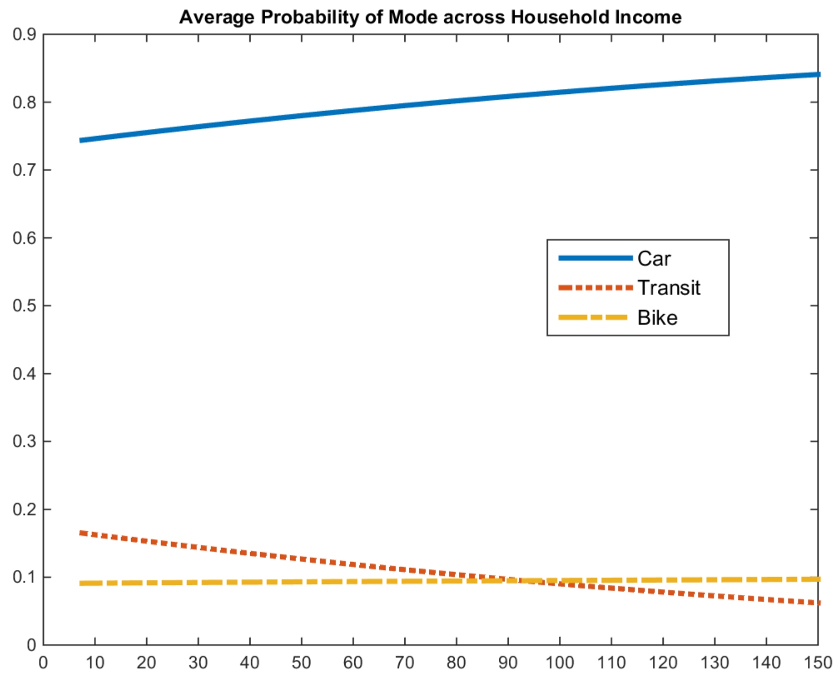
implies higher automobile usage and lower transit usage, but the total share of cycling remains constant.

The differential impact of age on mode choice can also be seen in Figure 6. Both cycling and public transit usage increase with age, but peak and then decline (a quadratic term for age is included in the model). Cycling as a mode of transportation can be physically demanding and the risk of serious injury increases with age, thus cycling mode choice peaks in the early 30s. Transit usage, however, peaks fairly late in life compared to cycling, in the later 50s.

Figure 7 compares the average probabilities of making complex trips between the complexity-component and crossing-components models. The average probability of making complex trips rises significantly across observable income for both models. Likewise, the average probability of making complex trips appears to peak with age around the same time for both models (mid 40s). However, the complexity-component model predicts a significantly higher probability of making complex trips at all levels of income and age. This gap represents a risk of significant bias relative to the less-restrictive specification that omits mode-specific error components, over-predicting commuters making complex trips across observed demographic characteristics and thus, indirectly, over-predicting car usage and under-predicting transit usage at all levels of these characteristics, as can be seen in Figure 8.

Finally, in a seminal mode-complexity study, Hensher and Reyes (2000) examine the change in mode shares predicted by a 10% increase in incomes. The authors find that a significant increase in income was associated with an increased propensity to make complex trips and thus a decrease in public transit usage. They conclude that trip complexity is a barrier to public transit usage, which conforms to the usual intuition. In the present study, changes in predicted shares from a 10% increase in incomes permits an assessment of the relationship between complexity and transit and also offers some insight as to whether complexity and cycling have such a relationship. Table 8 shows the changes in predicted probabilities from a 10% increase in incomes. The relationship between complexity and transit noted by Hensher and Reyes (2000) is repeated here.

For the crossing-components model estimates, car-simple, transit-simple, and even transit-complex shares drop significantly, and car-complex probability increases, as income increases. The increase in the predicted probability of car-complex is similar in magnitude to the decrease in predicted probabilities for the first three options. Recall that the estimates of the car and transit error components are not nearly as large as the estimate for the bicycling component. Nor are they statistically significant. This suggests that substitution between the car and transit options is easier than between bicycle and the



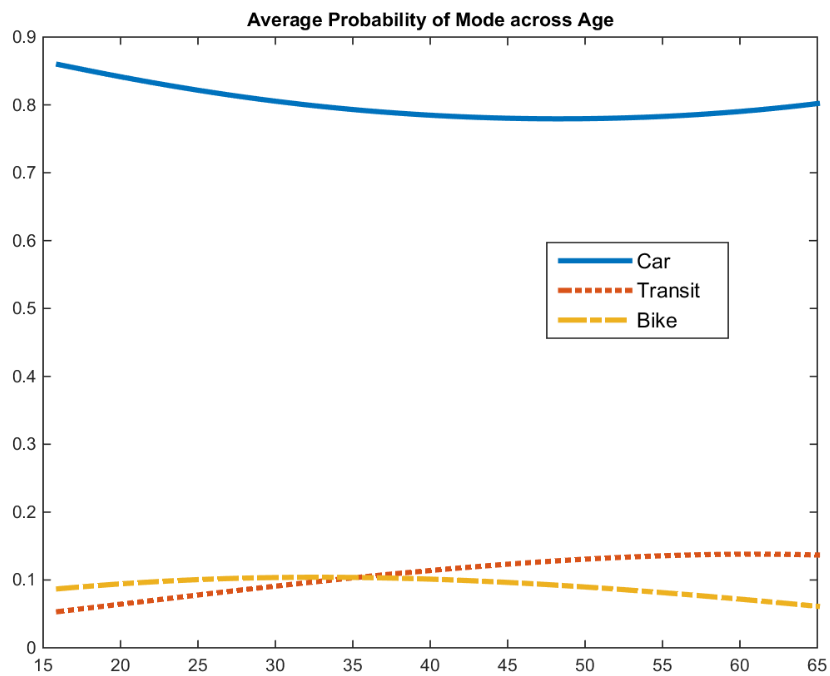


FIGURE 6. Average Mode Choice Probabilities for Crossing-Components Model

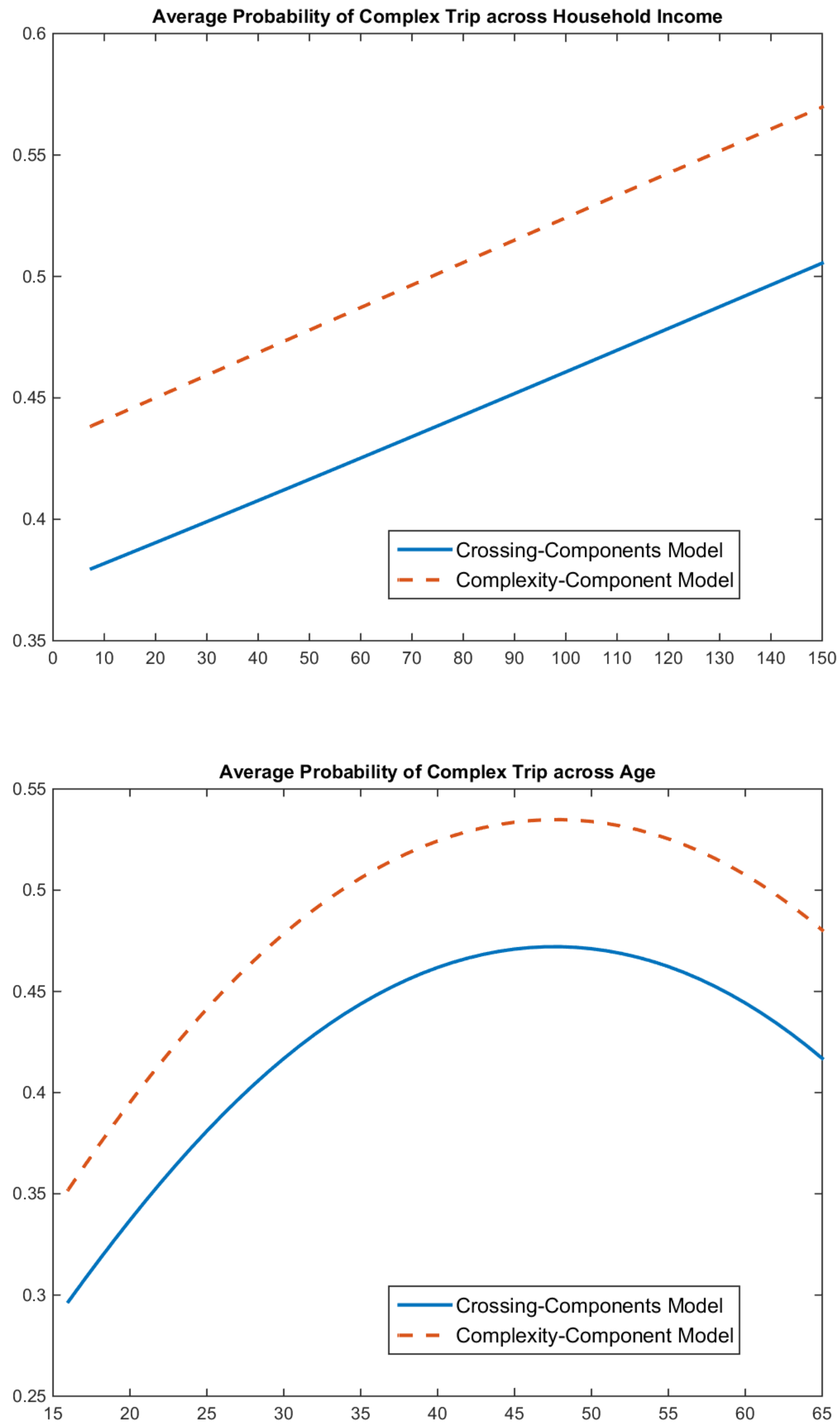


FIGURE 7. Average Complexity Choice Probabilities for Complexity-Component and Crossing-Components Model

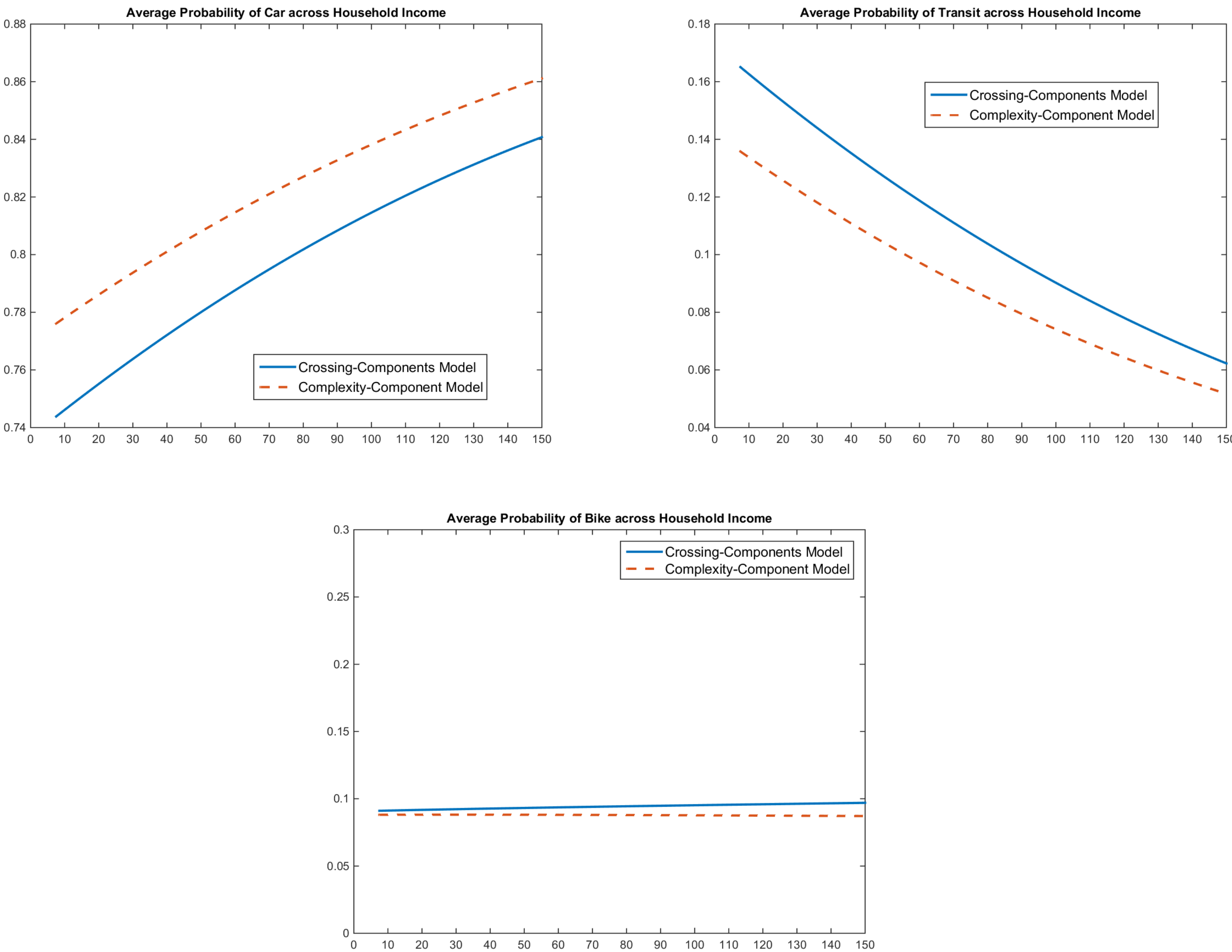


FIGURE 8. Average Mode Choice Probabilities for Complexity-Component and Crossing-Components Model

TABLE 8. Average Effects of a 10% Increase in Incomes

	Complexity-Component Model	Crossing-Components Model
Options	Change in Share (in % points)	Change in Share (in % points)
car-simple	-0.34***	-0.30***
	(.0998)	(.0969)
transit-simple	-0.25***	-0.29***
	(.0605)	(.0518)
bike-simple	-0.12**	-0.10**
	(.0512)	(.0481)
car-complex	0.74***	0.76***
	(.1160)	(.1270)
transit-complex	-0.12**	-0.18***
	(.0542)	(.0625)
bike-complex	0.08**	0.11***
	(.0494)	(.0430)
Mode Dimension		
car	0.40***	0.46***
	(.0739)	(.0851)
transit	-0.37***	-0.47***
	(.0499)	(.0485)
bike	-0.03	0.01
	(.0762)	(.0705)
Complexity Dimension		
simple	-0.71***	-0.69***
	(.0567)	(.0614)
complex	0.71***	0.69***
	(.0567)	(.0614)

*** p<0.01, ** p<0.05, * p<0.1

Note: Standard errors are bootstrapped.

other two mode options. Also, the predicted probability of bike-simple falls when income increases, but bike-complex rises by an approximately offsetting amount. This suggests that commuters are substituting from car-simple, transit-simple, and transit-complex to car-complex, whereas bike-simple commuters are substituting mostly to bike-complex. Thus, increases in desired trip complexity cannot necessarily be inferred to be a barrier to bicycle usage. Cyclists "stick to their gears" when they choose to make more-complex trips.

Conclusion

Choice studies concerning urban transportation modes have a significant role in informing public policy. They are crucial for assessing (1) the value of infrastructure improvements through predicting the use of modes of transportation, as well as (2) permitting the estimation of crucial parameters of consumer welfare such as the value of travel time (VOT). Modern transportation mode choice research has incorporated different dimensions of behavior that influence mode choices, such as trip complexity, which represent significant steps forward in the field. However, in a multi-dimensional choice setting greater care must be taken in the treatment of unobservable characteristics and the assumption that model errors are iid. As evidenced in this study, an error components logit (ECL) framework that takes into account the multi-dimensional structure of the choice of both mode and trip complexity can (1) reduce bias in VOT estimation, as well as (2) over-prediction of complex options across demographic characteristics.

Applying the estimated crossing components model to predict the mode changes resulting from a 10% increase in incomes illustrates substitution patterns between modes induced by consumers making complex trips. As found in previous studies, when consumers choose to make complex trips the are more likely to substitute away from public transit to driving cars. An open question has concerned whether bicycling exhibits this same pattern. I find that cyclists stick to their gears and consume more activities while riding their bikes, rather than substituting to a car. The predicted stability of the bicycling mode share with respect to a shift in incomes suggests that, compared to public transit, bicycling usage may be resilient to changing economic conditions. Policies aimed at increasing transit usage will have more difficulty achieving goals as changing income and demographics are more likely to influence usage of that mode. This study provides

TABLE 9. Complexity Component Model Demographic Parameters

	car-simple (base)	transit-simple	bike-simple	car-complex	transit-complex	bike-complex
VARIABLE	Coefficent	Coefficent	Coefficent	Coefficent	Coefficent	Coefficent
	(S.E.)	(S.E.)	(S.E.)	(S.E.)	(S.E.)	(S.E.)
Age		0.1451***	0.1520***	0.2570*	0.3147**	0.2393*
		(.0487)	(.0494)	(.1569)	(.1485)	(.1549)
Age^2		-0.0014***	-0.0017***	-0.0027**	-0.0031**	-0.0028**
		(.0005)	(.0006)	(.0016)	(.0016)	(.0016)
College degree		0.6746***	0.7582***	1.3451**	1.7577**	1.0750
		(.2370)	(.2186)	(.8019)	(.8746)	(.8610)
Household Income ($1000/yr)		-0.0116***	-0.0035*	0.0113*	0.0010	0.0123*
		(.0031)	(.0026)	(.0084)	(.0087)	(.0089)
Male		0.3986**	0.9081***	-0.8520*	-0.6148	-0.3806
		(.2081)	(.1909)	(.6263)	(.6724)	(.6884)
Household vehicles per person		-3.8459***	-2.7711***	0.0974	-4.2584***	-4.1133***
		(.3532)	(.3086)	(.2663)	(.4329)	(.4466)
Constant		-0.9098	-2.9582***	-6.9890*	-6.1585*	-5.2877
		(1.0186)	(1.0290)	(4.3679)	(3.9741)	(4.1310)

*** p<0.01, ** p<0.05, * p<0.1

TABLE 10. Mode Components Model Demographic Parameters

	car-simple (base)	transit-simple	bike-simple	car-complex	transit-complex	bike-complex
VARIABLE	Coefficent	Coefficent	Coefficent	Coefficent	Coefficent	Coefficent
	(S.E.)	(S.E.)	(S.E.)	(S.E.)	(S.E.)	(S.E.)
Age		0.1224**	0.0550	0.0877***	0.1867**	0.0371
		(.0551)	(.0944)	(.0195)	(.0622)	(.1023)
Age^2		-0.0012**	-0.0010	-0.0009***	-0.0017***	-0.0009
		(.0006)	(.0010)	(.0002)	(.0007)	(.0011)
College degree		0.7901***	0.8997**	0.5005***	1.1238***	0.4019
		(.2848)	(.4338)	(.0877)	(.3294)	(.4701)
Household Income ($1000/yr)		-0.0175***	-0.0041	0.0029***	-0.0125***	0.0048
		(.0044)	(.0048)	(.0010)	(.0046)	(.0053)
Male		0.4192**	1.7192***	-0.2408***	0.0411	1.1989**
		(.2436)	(.5210)	(.0761)	(.2656)	(.5458)
Household vehicles per person		-5.0222***	-5.9488***	-0.0438	-5.2760***	-7.1515***
		(.7647)	(1.5128)	(.0792)	(.7846)	(1.5174)
Constant		1.1655	-1.3253	-2.1864***	-1.1689	-0.6652
		(1.2049)	(1.9061)	(.4257)	(1.3599)	(2.0354)

*** p<0.01, ** p<0.05, * p<0.1

evidence that changes in income within a city may be less of a barrier that one might expect to policies aimed at increasing bicycle usage.

TABLE 11. Cross Complexity and Mode Components Model Demographic Parameters

	car-simple (base)	transit-simple	bike-simple	car-complex	transit-complex	bike-complex
VARIABLE	Coefficent	Coefficent	Coefficent	Coefficent	Coefficent	Coefficent
	(S.E.)	(S.E.)	(S.E.)	(S.E.)	(S.E.)	(S.E.)
Age		0.1953***	0.2258***	0.2932**	0.3595**	0.2712**
		(.0653)	(.0993)	(.1680)	(.1562)	(.1636)
Age^2		-0.0019***	-0.0027***	-0.0031**	-0.0035**	-0.0034**
		(.0007)	(.0011)	(.0018)	(.0017)	(.0018)
College degree		0.8369***	1.1275***	1.5093**	2.1198***	1.0679
		(.3044)	(.4507)	(.8575)	(.9709)	(.9251)
Household Income ($1000/yr)		-0.0165***	0.003	0.0124*	-0.0025	0.0148*
		(.0044)	(.0025)	(.0089)	(.0094)	(.0109)
Male		0.4806**	1.7393***	-0.9074*	-0.6265	0.1254
		(.2661)	(.4769)	(.6505)	(.7087)	(.9061)
Household vehicles per person		-4.6095***	-5.0067***	0.0757	-5.1731***	-6.9540***
		(.5968)	(1.1013)	(.2848)	(.7081)	(1.3460)
Constant		-0.8746	-5.3625***	-7.8754**	-6.1543*	-6.4025*
		(1.3275)	(2.2109)	(4.6082)	(4.0430)	(3.9549)

*** p<0.01, ** p<0.05, * p<0.1

CHAPTER IV

THE CONGESTION PREMIUM AND FLEX-TIME

Introduction

In traveling to work, consumers must choose when to leave and which transportation mode to use. Transportation modes have different attributes: bicycling requires physical exertion (and maybe a dry change of clothes), driving is convenient but parking may be costly, and public transit may be slow or involve long waits for transfers. These attributes can also change over the course of the day: bicycling in the dark is less safe, public transit service is more frequent during peak hours, and driving may be less attractive because of traffic congestion. This last feature—time wasted sitting in traffic—is a major source of lost productive time, totaling 6.9 billion hours in 2014 (Schrank et al., 2015). Time spent in traffic congestion can also be unpleasant. Given the choice between driving in free-flow traffic or in congested traffic for the same amount of time, all else equal, almost all commuters will choose to travel in free-flow traffic. The compensating differential between these two types of travel time is known as the "congestion premium." Unlike previous studies, I estimate the systematic variation in this congestion premium for commuters who have do or do not have flexible work schedules.[1]

I specify a two-dimensional choice of time of departure and transportation mode in a random coefficients logit model with error components across both dimensions. This empirical specification allows for heterogeneity across commuters in the disutility of free-flow and congestion travel times. The error components across time-of-departure and

[1] The Oregon Household Activities Survey (OHAS), which these data come from, asked respondents "Which of the following statements best describe your work schedule". Those considered to have flex-time for the purposes of this study agreed with the statement "I'm pretty much free to adjust my schedule as I like".

mode dimensions allow for correlation in unobservables within each of these dimensions, permitting more-flexible substitution patterns (Bhat, 1998).

The travel time data employed to identify the willingness to pay to diminish either free-flow or congested travel times have been calculated using an application programming interface (API) provided by Here Maps. There are a number of travel time calculation services provided on the Internet. Google Maps, Mapquest, Open Street Maps, and Here Maps are a few well-known examples. These services can be accessed through a web browser, one origin-destination pair at a time, or in bulk via API requests using software such as Python or R. These services provide highly accurate travel time data based on posted road speeds, loop detectors on major highways, and GPS or accelerometer data from users.[2] The benefit of using these data over the zone-to-zone approximated travel time or time on a major leg (i.e. a specific toll road) is that they provide very accurate door-to-door travel times, varying across times of departure, that are based on real-time and historic inputs.

Using an estimated error components logit (ECL) model, I find a congestion premium that is approximately 30% of the value of travel time (VOT). This result is in line with previous studies. However, I extend this model to include an indicator for whether commuters have flexible work schedules and allow the estimated congestion premium to vary with this commuter attribute. The estimated congestion premia for commuters with and without flex-time are approximately 0% and 80% respectively. This implies that a very significant component of the congestion premium could stem from the uncertainty about one's ability to arrive at work on time when traveling in congestion.

[2]Many APIs have data usage limits or trial periods for the free service and a very high marginal cost beyond the limit (e.g., Google Maps API permits 2500 requests a day but requests beyond this limit or access to travel time in congestion require the purchase of a $10,000 data plan). Terms of service also frequently change in terms of what attributes are accessible. These issues often create situations where researchers who rely upon APIs to measure travel times for alternatives in consumers' choice sets have to often switch between APIs.

If commuters with flexible work schedules have a lower dis-utility of driving in traffic congestion, then they may be incentivized to drive during peak times if they prefer that alternative over traveling in the early morning. An examination of the marginal effect of flex-time on mode and time-of-departure choices reveals that, although commuters with flex-time would be more likely in the aggregate to take alternative transportation, these commuters are 6.5% more likely to travel during peak hours and 3.5% more likely to *drive* during peak hours. Thus, policies aimed at increasing the penetration of flexible work start times in urban areas may, unexpectedly, increase peak period traffic congestion. This is because commuters substitute away from traveling in the early morning hours to peak hours, (7:00 am to 9:00am) while very few substitute toward traveling in the offpeak morning hours (after 9:00 am).

In the following section, I briefly describe the vast body of research on VOT as well as a more focused review of research into the congestion premium. In the third section, I detail the random coefficients logit with error components specification I use to estimate free-flow VOT and the congestion premium. In the fourth section, I describe the ODOT data and the travel times collected via Here Maps. In the fifth section, I estimate the random coefficients logit with error components specification and describe the VOT and congestion premium implied by the estimated parameters. Lastly, I conclude by discussing the implications of these results and outlining some possible future avenues of research into the potential commuting-choice impacts of flexible work schedules.

Background

Urban transportation mode choice has been an active area of research since Daniel McFadden's seminal work on the Bay Area Rapid Transit (BART) System. Two major motivations for this research are prediction of the usage of new modes (e.g., BART) and welfare analysis of policy changes (e.g., construction of more road capacity or changes in transit fares). Small (2012) reviews the modern VOT literature and finds that, even after significant and fruitful study for decades, there remain many dimensions of the heterogeneity of VOT that are still poorly understood.[3] Abrantes and Wardman (2011) offer a meta-analysis that summarizes a large number of studies estimating VOT and highlights the consistent findings and patterns in results.

Estimating VOT requires a wealth of travel time data on options chosen as well as those not chosen. The travel times for the alternatives not chosen can be imputed from known geographic zone-to-zone times or measured for specific major segments of the trip that are shared by many commuters. Door-to-door travel times for alternatives not observed to be chosen by commuters in revealed preference data can be difficult to construct. However, these data are important for accurately estimating the value of travel time (VOT) and the congestion premium. Peer et al. (2013) demonstrate the necessity of accurate door-to-door travel time data in estimating VOT. The authors find that zone-to-zone or major-segment-only travel time data tend to lead to overestimates of VOT. This is because neglecting the entire travel time door-to-door biases the parameter estimates of the disutility of travel time upward. Intuitively, the measurement of major leg or zone-to-zone time is biased downward from the true door-to-door time, therefore observed switches fro time of day or mode induced by inaccurately small changes in travel time will translate into a much higher estimated disutility of that travel time.[4]

As stated earlier, there has been significant research designed to estimate the VOT (the value of free-flow travel time). However, the additional disutility of driving in traffic congestion has been examined in only a handful of studies. The few existing studies

[3]VOT is also often refered to as the value of travel time savings (VTTS). Specifically, VOT or VTTS is the consumers' willingness to pay for a reduction in the time it takes to travel to their desired destination.

[4]This intuition is, in fact, empirically demonstrated by Lam and Small (2001). They find that when they included the travel time outside the ten-mile major leg being investigated the estimate VOT fell by 50%.

have found the congestion premium to be approximately 25% to 50% of free-flow VOT, as mentioned in Small (2012). This premium has been attributed to a higher disutility from having to pay closer attention to the road in order to avoid collisions, but also to the uncertainty of the additional travel time required to complete the trip. Steimetz (2008) decomposes these factors in a toll road setting and finds that disutility from increased collision risk and the effort needed for collision avoidance contributes just as much to welfare loss as the additional time cost of traffic congestion. However, the congestion premium appears not yet to have been examined in a broad revealed preference setting including door-to-door travel time data.

Examining the congestion premium in a revealed preference setting with accurate peak vs. off-peak travel time data is especially important because the congestion premium is difficult to identify in a stated preference setting. Rizzi et al. (2012) find in a stated preference experiment that consumers making route decisions based on free-flow travel time, congested travel time, and toll price attributes do not exhibit a congestion premium unless pictures of crowded streets are included in the descriptions of alternatives that have traffic congestion. The disutility of driving in traffic congestion appears not to be salient to consumers unless they will experience it in a real setting or are reminded of it in an experimental setting. When these pictures are included, Rizzi et al. (2012) find a congestion premium of approximately 30%.

In general, joint mode choice and time of departure (TOD) studies inform policy-making by identifying the relative sensitivity of switching in both dimensions. If commuters are more willing to switch modes in response to price or travel-time changes, then transit infrastructure investment or fare reductions will be more effective for alleviating congestion. If commuters are more willing to adjust the time at which they travel, then congestion pricing or the promotion of employer flexible schedule policies will be more effective. Greater knowledge of which commuters are more likely to switch between modes is also helpful for policy-making. For example, Anderson (2014) argues that a transit shutdown in Los Angeles had such a significant impact on congestion because those commuters with the greatest marginal contribution to congestion were also the ones more highly incentivized to take transit.

To estimate the separate values of free-flow and congested time, I approach the joint mode and time-of-departure decision as a three-way mode choice combined with a four-way time of departure choice over discrete intervals of time. Limiting the time of departure choice to discrete time periods in the model is a common approach and has been used frequently in the literature. Hess et al. [2007, pg. 4] discusses numerous time-of-departure studies that use discrete time periods. Some studies additionally include the displacement from the preferred arrival time that a given departure time may cause (i.e. modeling the disutility of early or late arrival), known as the "bottleneck" model. The ODOT data, unfortunately, do not include consumers' preferred arrival times. Models used in forecasting settings cannot make use of preferred arrival time information either, however, and rely on alternative-specific constants instead, but researchers have to be parsimonious concerning the number of TOD options as identification of distinct constants for each interval becomes difficult (as explained in Hess et al. (2005)). Also, when a commuter has a flexible work schedule, then the importance of the preferred arrival becomes less clear.

My contribution to this literature is the use of a revealed preference dataset with door-to-door travel times in peak and off-peak times of day and an investigation into systematically varying heterogeneity in the congestion premium. In the logit model, I include error components that take into account correlations in unobservables across both mode and time-of-departure (TOD) dimensions. I find a congestion premium that is equivalent to what is estimated in previous studies (approximately 30% greater than free-flow VOT). Additionally, I allow the indicator for whether the consumer has a flexible work schedule (flex-time) to be interacted with congestion, to differentiate the congestion premium accodring to the individual's type of work schedule. This differentiation produces an even higher congestion premium (of approximately 80%) for those without flexible work schedules. Interestingly, however, those with flexible work schedules are found to have almost no disutility of driving in traffic congestion compared to that of driving in free-flow traffic.

Conceptual Model

The choice of mode in this model is limited to driving, riding transit, or bicycling. I include a set of individual characteristics along with travel time differentiated into four discrete time periods. The utility for option j in a standard multinomial logit setting is:

$$U_{ij} = \alpha_f \text{total travel time}_{ij} + \alpha_c \text{congested travel time}_{ij} + \gamma \text{ price}_{ij} + \beta_j' x_i + \varepsilon_{ij}.$$

The systematic portion of utility is:

$$V_{ij} = \alpha_f \text{total travel time}_j + \alpha_c \text{ congested travel time}_j + \gamma \text{ price}_j + \beta_j' x_i$$

where j is a mode-and-time of departure choice, $j \in C$. The total and congested travel times are separated and their disutilities, α_f and α_c, are thus permitted to differ. As the total travel time, both free-flow and congested, is included, α_c identifies just the disutility component of the congestion premium. The congestion premium being the "extra" amount that commuters are willing to pay to alleviate a congested unit of time compared to free-flow time. The parameter γ is the disutility of the price of the mode (i.e. the negative of the marginal utility of net income). The choice-specific parameter vector,

β_j, and observable characteristics of individuals, x_{ij} are multiplied and added with the unobservables. In a standard logit model, the unobservable characteristics, ε_{ij} are assumed to be independent and identically distributed extreme value (type I). Thus the resulting expected probability of individual i choosing mode-and-time combination j is:

$$P(ij) = \frac{e^{V_{ij}}}{\sum_{h \in C} e^{V_{ih}}}$$

This independently and identically distributed assumption for ε_{ij} can be restrictive. As the estimation of the choice model is based on differences in scaled utility, the unobservable components are defined by observed differences in choice characteristics and preferences. If there is a common unobserved component shared by two or more options, but this component is ignored, then the maintained iid assumption will be violated. More-flexible error structures can be used, in this case, to allow for correlations among the unobservables.

Some examples of things that are unobservable in this setting but may impact the mode decision include: local congestion, the commuter's health conditions, or the nature of the nearby built environment. These are examples of unobservables that may have a strong impact on the choice of car, transit or bike for a single individual, but are not available to be included in these data. These unobservables may be specific to modes but are shared across choices involving any one mode because there is a TOD-specific option within each mode option. After reflecting on these examples, it is plausible and even likely that the iid assumption is violated in this case. A significant determinant of the time-of-departure choice that is unobserved in these data is the employer's required work start time (however, flexibility of the individual's work schedule is observed). Thus, a more-general error structure should be used, to allow for correlation between unobservable characteristics of different alternatives. This can be accomplished with a random coefficients logit choice model (also known as random parameters logit or mixed logit) with error components.

A suitable error components logit specification allows for commuter i to have utility from option j given by:

$$U_{ij} = \alpha_f \text{ free-flow travel time}_j + \alpha_c \text{ congested travel time}_j + \gamma \text{ price}_j + \beta_j' x_i + \eta_{\text{i,mode}} + \eta_{\text{i,time}} + \varepsilon_{ij} \tag{4.1}$$

where the parametric families for the functional form of the distributions of $\eta_{\text{i,mode}}$ and $\eta_{\text{i,time}}$ are selected by the researcher. This distribution is designated as the mixing distribution, f, the parameters of which, θ, are estimated (i.e., the mean and variance for the normal case). The choice probabilities can be expressed as:[5]

$$P_{ij} = \int \left(\frac{e^{V_{ij}(\eta_{\text{mode}}, \eta_{\text{time}})}}{\sum_h e^{V_{ih}(\eta_{\text{mode}}, \eta_{\text{time}})}} \right) f(\eta_{\text{mode}}, \eta_{\text{time}} | \theta) d\beta \tag{4.2}$$

In very general terms, the utility of commuter i choosing option j can also be cast as an error components specification:[6]

$$U_{ij} = \alpha_{fi} \text{ free-flow travel time}_j + \alpha_{ci} \text{ congested travel time}_j + \gamma \text{ price}_j + \beta' x_{ij} + \eta_i' z_{ij} + \varepsilon_{ij} \tag{4.3}$$

where η_i is a vector of (normally distributed) error components, with zero mean and a variance to be estimated, and z_{ij} includes dummy variables that are equal to one if and only if the error component in question is included in the utility for option j.[7]

[5]See Train [2009 Ch. 6] for discussion of different mixing distributions that can be used.

[6]Note that this specification does not rule out random β parameters. If the researcher wishes to allow the coefficient of a specific observable vary randomly then z_{ij} can simply be augmented to include the data related to that parameter.

[7]Note that if α_c and α_f are assumed to be fixed and z_{ij} is modified to include travel time data that the specification has, in fact, not been changed.

Error components and random parameters are effective in that they allow for more-flexible substitution patterns between the choices, as explained in Hess et al. (2007). I include error components for each option in both dimensions of the choice set—mode and time-of-departure—to allow for greater flexibility and to identify the choice structure. Including error components to represent each dimension of a choice set has been found to be important for a number of reasons. It achieves a better fit to the data. It provides more insight into the choice structure. Lastly, it controls for bias caused by dimension-specific unobservables being correlated with observables of interest. Bhat (1998) finds that error components included for each option in each dimension of the choice set ("crossing components") are significant in a joint mode and time-of-departure choice setting, similar to the model examined here. In this study, however, congestion time during peak morning hours is included and the joint mode and time-of-departure choice allows for the estimation of the congestion premium. In the previous chapter of this dissertation, for the joint choice of mode and trip-complexity, I find that failing to include error components across the mode dimension (in addition to the complexity dimension) leads to a significant bias downward in the estimated value of travel time.

Data

The primary data on mode choice come from a large, detailed, and confidential survey called the Oregon Housing Activities Survey (OHAS), fielded by the Oregon Department of Transportation (ODOT) in 2011. The survey includes a wealth of demographic information about each commuter and his or her household. Variables include, for example, income, age, gender, whether the commuter's employer pays for parking, and whether the commuter's employer provide a transit pass. These data pertain to the Portland metropolitan area (including Vancouver, WA) and focus solely on work

TABLE 12. Summary Statistics of Commuters by Mode Chosen

	Car	Transit	Bike
SHARES	85.50%	9.30%	5.18%
VARIABLES	Mean	Mean	Mean
	(S.D.)	(S.D.)	(S.D.)
Age	44.53	43.17	42.13
	(12.75)	(14.01)	(10.56)
Household Income ($1000/yr)	81.10	56.25	74.75
	(41.41)	(37.94)	(43.41)
Male	0.495	0.468	0.681
	(0.500)	(0.499)	(0.467)
Employer provided free parking	0.831	0.404	0.723
	(0.374)	(0.491)	(0.448)
Employer provided transit pass	0.092	0.220	0.142
	(0.290)	(0.415)	(0.350)
Free flow drive time	18.39	18.75	12.36
	(11.97)	(8.85)	(6.01)
Congested drive time	21.08	22.63	13.78
	(14.46)	(11.17)	(7.62)
Transit time	67.30	52.13	41.41
	(39.69)	(22.68)	(20.49)
Bike time	53.63	50.60	13.78
	(50.19)	(33.48)	(17.91)
Price of Drive	6.42	8.88	4.36
	(5.68)	(1.94)	(3.63)
Price of Transit	2.26	1.94	2.14
	(.725)	(1.03)	(.876)
Price of Bike	0.919	.829	.425
	(.893)	(.547)	(.304)
N=3458			

trips. There are 3,458 commuters in the sample who were surveyed over multiple months in 2011.

The ODOT survey also includes extremely detailed spatial origin-destination data. I use the spatial coordinates of home and work locations to compute travel times and distances traveled for each trip, for alternate travel modes.[8] In addition to off-peak travel times where traffic is free-flowing, I include peak travel times where there is traffic congestion via the HereMaps API which permits requests for the travel time reflecting traffic at the time the information is requested. The price of driving is approximated by multiplying the distance traveled in miles while driving by $0.585/mile, based on AAA

[8]The coordinate data is processed via API requests from Here Maps. These requests were based on the MQtime codebase, Voorheis (2015)

TABLE 13. Summary Statistics of Commuters by Time-of-Departure Chosen

	Early AM	Peak AM	Offpeak AM	Offpeak PM
SHARES	32.42%	50.69%	10.80%	6.09%
VARIABLES	Mean	Mean	Mean	Mean
	(S.D.)	(S.D.)	(S.D.)	(S.D.)
Age	44.63	44.03	46.62	43.70
	(12.35)	(12.16)	(13.58)	(14.85)
Household Income ($1000/yr)	77.65	85.35	63.14	65.10
	(39.90)	(41.55)	(41.89)	(40.51)
Male	0.561	0.473	0.443	0.538
	(0.496)	(0.499)	(0.497)	(0.499)
Employer-provided free parking	0.788	0.768	0.783	0.836
	(0.408)	(0.421)	(0.412)	(0.370)
Employer-provided transit pass	0.137	0.115	0.065	0.041
	(0.344)	(0.319)	(0.247)	(0.200)
Free flow drive time	21.76	17.08	16.21	15.36
	(12.87)	(10.84)	(9.62)	(10.65)
Congested drive time	25.39	19.55	18.41	17.64
	(15.38)	(13.19)	(11.92)	(12.96)
Transit time	75.42	61.56	59.50	53.94
	(41.29)	(36.02)	(37.30)	(34.22)
Bike time	65.17	47.64	44.80	43.99
	(55.32)	(44.84)	(38.67)	(45.16)

N=3458

(2011), and also adding the approximate daily cost of parking in downtown Portland if the cost of parking (approximately $7/workday) is not provided by the commuter's employer. The price of cycling is approximated by multiplying the distance traveled while cycling by $0.10/mile, according to Litman (2013). The price of transit in the city of Portland is $2.50 for a one-way trip, or $0 if the commuter's employer provides a free transit pass.

Table 12 contains summary statistics for these commuters by mode chosen. Without conditioning on other observables, age does not appear to differ significantly between those who choose to drive, take transit, or ride a bicycle. Those who drive tend to have the highest incomes on average, while those who bike tend to be in the middle. Those who take transit tend to have the lowes (so, this suggest an important price effect of paying for parking). Bicyclists are much more likely to be male.

The four time-of-departure options are: Early AM (12:01-7:00), Peak AM (7:01-9), Off-peak AM (9:01-12:00), and Off-Peak PM (12:01-3:00). Too few respondents departed

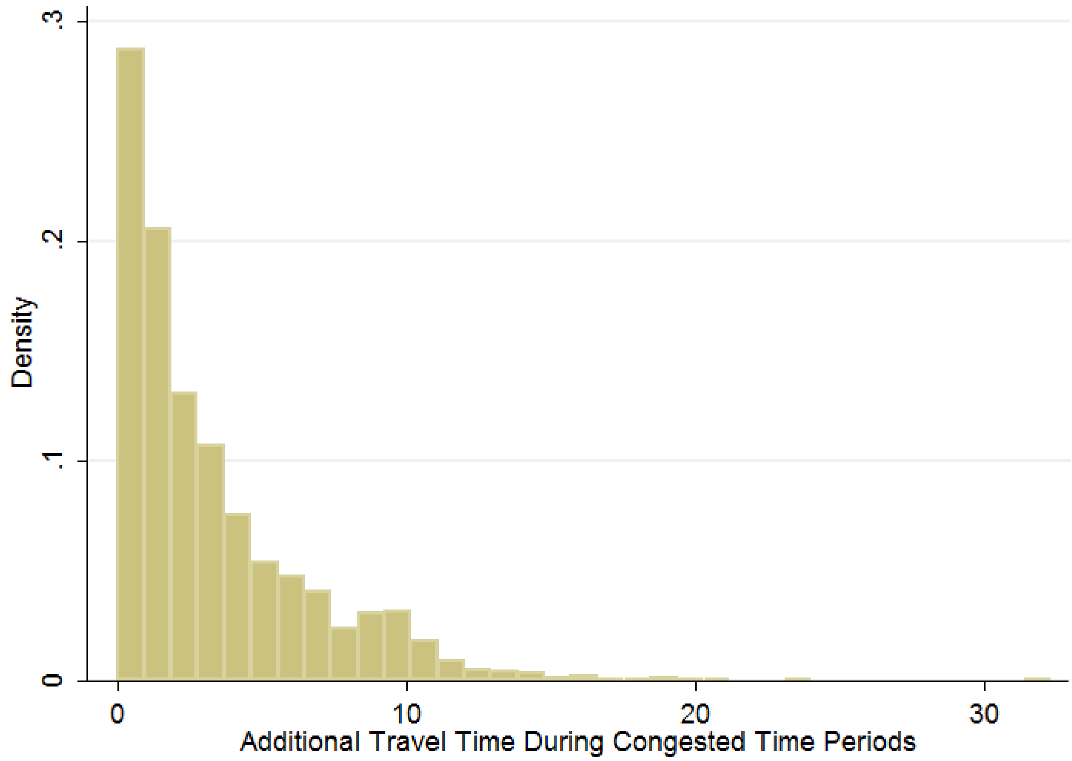


FIGURE 9. Congestion Data

after 3 p.m. and used transit or bicycled to include in the analysis. Table 2 contains summary statistics of commuters by the time of departure chosen. Commuters who depart in the AM tend to have higher incomes than those at other times. Commuters who depart in the Peak AM and OffPeak AM are more likely to be female than commuters who depart at other times.

Figure 9 contains a histogram of the additional travel time caused by traffic congestion captured in the data. One can see that additional congestion time on the way to work tends to be small (below 7 minutes) for a significant portion of the population, but there is a nontrivial proportion of the population that faces 10 or more minutes of additional travel time in traffic congestion if they choose to travel during peak hours.

TABLE 14. Error Components Logit Model Estimation with Error Components

	I	II
Parameters	Estimate (S.E.)	Estimate (S.E.)
Free Flow Travel Time	-.0676 ***	-.0632 ***
	(.0068)	(.0118)
Free Flow Travel Time x Flex Time		-.0105
		(.0087)
Additional Congested Travel Time	-.0222	-.0545 **
	(.0173)	(.0290)
Additional Congested Travel Time x Flex Time		.0530 **
		(.0293)
Price	-.1817 ***	-0.1914 ***
	(.0198)	(.0367)
VOT (derived)	22.32	19.81
Congestion Premium (derived)	7.33	17.08
Log-Likelihood	5101.63	5067.33
Mode and T.O.D. Error Components	Yes	Yes
Alternative Specific Constants	Yes	Yes
Demographic Controls	Yes	Yes
Flex Time Controls	No	Yes

*** p<0.01, ** p<0.05, * p<0.1

Results

The mixed logit model discussed in the conceptual section is estimated via simulated maximum likelihood (SML). Parameter estimates of interest as well as the calculated values of the VOT and the congestion premium (derived from travel time and price utility parameters) are included in Table 14. Both specifications include error components across both dimensions of the choice set. Specification I estimates the VOT and congestion premium. Specification II then extends the specification to include option-specific flex-time shifters in addition to interactions between the indicator forflex-time and the two types of travel time.

Value of Travel Time and the Congestion Premium

The two specifications reported in 14 both include demographic controls. In the first specification, the congestion premium appears to be approximately 30% on top of the free-flow VOT. However, once these coefficients are allow to differ according to whether the commuter has a flexible work schedule, the congestion premium increases to greater than 80% of free-flow VOT. However, the coefficient on the interaction of additional travel time from congestion and flex time is significant and bear the opposite sign from the basic congestion premium. This provides strong evidence that the additional disutility of driving in traffic congestion is diminished for commuters who have flexible start times at work. Option-specific flex-time controls are included, so this coefficient is estimated while controlling for the propensity of commuters with flex-time to travel at different times of day or by different modes, all else equal.

I have found that those with flex-time value the additional time traveling in congestion approximately the same as that of traveling in free-flow, but those who do not have flex-time have a very high disutility of additional travel time in traffic congestion. Estimating these two groups' congestion premia together, without differentiation, leads to a much lower estimate.

Mode and Time-of-Day Choice

Table 15 contains the estimated marginal effects of instantaneous (0 to 1) changes of the continuous (discrete) variables included in the error components logit model on the probability of choosing a mode or time of departure. These effects are calculated for each observed commuter and averaged over the entire dataset.

The impacts of changes in mode-specific travel times and prices have the expected signs. An increase in the price or travel time for a mode decreases its own probability and

TABLE 15. Average Marginal Effects on Aggregated Mode or Time of Departure Choices

VARIABLE	Drive	Transit	Bike	Early AM	Peak AM	OffPeak AM	OffPeak PM
Instantaneous Marginal Effect							
Travel Time Drive	-0.00392	0.00211	0.00180	0.00015	-0.00018	0.00002	-0.00000
Travel Time Transit	0.00207	-0.00224	0.00017	-0.00022	0.00023	-0.00001	0.00000
Travel Time Bike	0.00177	0.00017	-0.00194	0.00006	-0.00005	-0.00001	0.00000
Congested Time	-0.00251	0.00127	0.00123	0.01235	-0.01300	0.00065	0.00000
Price Drive	-0.01232	0.00664	0.00568	0.00050	-0.00058	0.00008	-0.00000
Price Bike	0.00536	0.00051	-0.00588	0.00020	-0.00016	-0.00003	0.00000
Price Transit	0.00628	-0.00680	0.00051	-0.00067	0.00071	-0.00003	0.00000
Income	0.00104	-0.00097	-0.00006	-0.00058	0.00105	-0.00047	-0.00000
Age	-0.00342	-0.00139	0.00481	0.00639	-0.00559	-0.00072	-0.00007
Discrete Marginal Effect							
Flex Time	-0.04597	0.02988	0.01608	-0.08424	0.06582	0.01854	-0.00012
Male	-0.04874	0.01345	0.03529	0.08704	-0.07999	-0.00722	0.00017
College	-0.03522	0.01538	0.01984	-0.12293	0.11474	0.00841	-0.00021

increases the probability of the other modes being selected. However, the magnitudes of these marginal effects vary. An increase in the price or travel time of driving decreases the probability of driving and has corresponding increases in probability of riding transit or bicycling. However, an increase in the travel time or price of transit or bicycling will produce a corresponding increase in the probability of driving but a negligible increase in the other alternative mode option.

The marginal effects of income and male also have the expected signs, given previous research. Higher-income commuters are more likely to drive and less likely to take transit, but there is little impact on the probability of bicycling. Males are much more likely to bicycle and also more likely to commute in the early a.m. hours than females. College educated commuters are a little more likely to take alternative modes of transportation but much more likely (11%) to travel during the peak a.m. hours than the early a.m.

The parameter of the interaction between congestion time and flexible work schedule demonstrates that the congestion premium is not significantly different from zero for commuters with flexible work schedules. Thus, the disutility of driving in traffic congestion is far lower for commuters with flexible work schedules. To control for the direct effects

TABLE 16. Average Marginal Effect of Flex Time

FLEX TIME	Drive	Transit	Bike
Early AM	-0.09606	0.00982	0.00199
Peak AM	0.03573	0.01709	0.01299
OffPeak AM	0.01447	0.00296	0.00110
OffPeak PM	-0.00012	0.00000	-0.00000

of flexible work schedules on choice, holding price and travel times fixed, flexible work schedule parameters for each mode and time of departure were also included in the model (excluding driving and peak a.m., for normalization reasons). The average marginal effects of flexible work schedules are computed from a discrete change from 0 to 1 across the entire dataset. Based on the results reported in Table 15, commuters with flexible work schedules are more likely to take alternative transportation modes than to drive. However, they are also likely to substitute away from traveling in the early a.m. to traveling during peak a.m. hours and, to a much smaller extent, the offpeak a.m. hours.

Given that commuters with flexible work schedules have a lower disutility of driving in traffic congestion, and that they appear to be more likely to travel during peak hours, it is important to examine the impact of a flexible work schedule on each separate Mode-TOD alternative. These additional peak a.m. commuters may be riding transit or bicycling, or they may be driving, if they have a lower disutility of driving in congestion. Table 16 contains the average marginal effects of a flexible work schedule on the probability of choosing a specific Mode-TOD combination. There is an over 9% decrease in the early a.m. hours of the probability of choosing to drive. The probability of riding transit or bicycling does rise, but almost exclusively in the peak a.m. hours, with the probability of driving during the peak a.m. hours increasing by about twice the amount, 3.5%.

These results enlighten the potential effects of increased work-schedule flexibility for urban employees. Encouraging more flexible work schedules for the purpose of promoting the use of alternative modes and alleviating traffic congestion may, in fact, have the unintended consequence of increasing the proportion of commuters driving during peak hours and increasing traffic congestion. A significant component of the congestion premium is believed to be the increase in the uncertainty of the travel time to work during times of congestion. Allowing for flexible work schedules eliminates the disutility from the uncertainty of driving in congestion and provides a perverse incentive for commuters to travel during congested time periods when they may not have done so before. The intention of promoting flexible work schedules would be that commuters will be more likely to take alternative modes of transportation or substitute to traveling during the offpeak a.m. hours, but it appears that the change in the preference for driving in traffic congestion could induce far more commuters who drive in the early a.m. to now drive during peak a.m. hours. The probability of driving, in the aggregate, decreases and use of alternative mode of transportation increases which, in general, is associated with a decrease in traffic congestion. However, aggregate automobile usage that is not the only relevant measure to traffic congestion. When commuters are driving their automobiles also matters. Regardless of mode share changes during the offpeak hours, if automobile usage increases during peak hours, then traffic congestion will increase as well.

Conclusion

I have developed and estimated a mode and time-of-departure choice model where unobservables in the utilities of different alternatives are permitted to be correlated across both the mode and time-of-departure dimensions. This reduces the potential for bias in the estimation of the coefficients caused by a violation of a maintained assumption of independent and identically distributed unobservables.

The ODOT data have been augmented with travel time information obtained from Google Maps and HereMaps application programming interfaces. These travel times are door-to-door and include estimates of travel time in congestion during the peak AM commute period. These data permit estimation of the additional disutility of travel time caused by travel congestion, termed the congestion premium, in a revealed preference setting with multiple modal options.

This research contributes an estimate of the congestion premium, but also broadens our understanding of different types of heterogeneity in VOT by demonstrating that there is significant heterogeneity in the congestion premium associated with whether the commuter has a flexible work schedule. The undifferentiated estimate of the congestion premium using an error components specification was 30% of VOT (within the typical range typical in the literature). However, differentiating this premium according to whether the commuter has a flexible work schedule, I find that the congestion premium is near 0% when the commuter has flex-time and roughly 80% when the commuter does not enjoy a flexible work schedule. This could point to significant variation in the effectiveness of different transportation policies designed to alleviate traffic congestion, depending on what proportion of the population has flexible work schedules. As previously referred to, Small (2012) highlights that many dimensions of the heterogeneity of VOT have yet to be explored. This is true for the congestion premium as well. One could examine many additional dimensions of the congestion premium. For example, is having a more luxurious car associated with being willing to spend more time in traffic?

Lastly, the marginal effects of flexible work schedule on mode and time of day choice are evaluated. The greater flexibility of work schedules induces more alternative transportation use, which is generally a significant goal of policy-makers. However, the associated decrease in the congestion premium with flex-time implies that these commuters are also more willing to drive during peak hours, contributing more to congestion. This provides evidence that to encourage more widespread flexible work schedules in urban workplaces may, in fact, have unintended consequences. It has been shown in previous research, such as Anderson (2014), that a very small change in the proportion of transit usage can have a large impact on traffic congestion. Thus, the overall effect of flexible work schedules on traffic congestion may be ambiguous, as there is both increased transit usage overall as well as increased automobile usage during peak hours. Further research to examine the relative impacts of these decisions could reveal whether increasing the proportion of flexible work schedules would generate a net benefit or a net loss in an urban area.

CHAPTER V

CONCLUSION

The three substantive chapters of this dissertation discuss decision-making by consumers located in space. These chapters also examine decisions that must be made over multiple dimensions, is either in a strategic game, or by consumers making transportation decisions, and the relevance of these additional spatial dimensions to results of the analysis. Each of these chapters makes an original contribution to its respective literature and also illuminates the promise of further inquiry.

In the second chapter, voters' ideal policy preferences are distributed over a policy space and they vote for candidates based on each candidate's proximity to their ideal point in policy space and each candidate's allocation of some non-policy resource to their electoral district. The resulting analysis demonstrates that the existence of this additional strategic dimension can result in the divergence of the policy positions of candidates in equilibrium. This analysis is constrained in that it examines only pure strategy equilibria. When candidates' resources are closer to parity then pure strategy equilibrium do not exist. Therefore, examining equilibria when candidates have similar resources may require evaluating mixed strategies or plausible extensions in order to be applied to contests between candidates with more-similar resource constraints.

In the third chapter, I examined the joint decision of travel mode and trip-complexity and find that taking into account unobserved preferences for specific options is important for accurately estimating the value of travel time. I also found that the well-known connection between transit, driving mode choice, and trip-complexity does not hold for bicycling and driving mode choices. Early work in the trip-complexity and mode decision literature has found that increases in trip-complexity are predicted to cause a corresponding drop in public transit usage and an increase in driving (as driving is a more-convenient mode for complex trip making). I find that this relationship does not hold between driving and bicycle usage. The predicted probability of complex trip-making increases for bicyclists—they stick to their gears and do not substitute away to driving. This implies that if travel times and the built environment are sufficient to induce commuters to bicycle, those bicycling mode shares will be robust to demographic or other changes that impact complexity and would typically cause substitution away from transit usage.

In the fourth chapter, I augmented the Oregon Housing and Activities survey with information about driving time during congested time periods calculated by Here Maps. Using these data, I estimate the additional disutility of driving in traffic congestion, relative to that of driving in free-flow traffic (the congestion premium). In a novel specification, I allow the congestion premium to vary between workers with flexible work schedules and those without. I find that commuters with flexible work schedules do not have a congestion premium that is significantly different from zero, while the congestion premium for those with inflexible work schedules is 80%. Thus, the disutility of driving during peak morning commute hours is much lower for those with flexible work schedules. The model predicts that when a commuter has a flexible work schedule, they become much more likely to use alternative modes of transportation over all time periods. However, the propensity to drive during peak hours actually increases. Thus, encouraging employers providing flexible work schedules for commuters would be predicted to have the unintended consequence of incentivizing more driving during peak morning commute hours and possibly a corresponding increase in traffic congestion (the ambiguity in this case stems from the higher alternative mode usage).

Both of the third and fourth chapters of this dissertation examine dimensions of transportation decision-making in addition to, and in connection with, mode choice. Both of these dimensions of urban transportation decision-making could have significant implications for policy-making. Recent influential studies of urban transportation, such as Parry and Small (2009) and Anderson (2014), make use of a generalizable and replicable computable general equilibrium (CGE) model of transportation for a given urban area where congestion is endogenized and other externalities associated with automobile use can be calculated. These models take as inputs the key parameters of transportation decision-making, like those estimated in the third and fourth chapters of this dissertation. However, these CGE models remain to be extended to include complex trip-making and the additional disutility of driving in traffic congestion (other than that of free-flow time). The implications of these more-complex views of transportation decision-making can be investigated further with extensions to these CGE models. Examining the impacts of these extensions on simulations of the benefits of changes in transit fares and other policy changes and are important next steps for this research.

REFERENCES CITED

AAA (2011). Your driving costs. Website.

Abrantes, P. A. and Wardman, M. R. (2011). Meta-analysis of uk values of travel time: An update. *Transportation Research Part A: Policy and Practice*, 45(1):1–17.

Anderson, M. L. (2014). Subways, strikes, and slowdowns: The impacts of public transit on traffic congestion. *American Economic Review*, 104(9):2763–2796.

Bhat, C. R. (1997). Work travel mode choice and number of non-work commute stops. *Transportation Research Part B: Methodological*, 31(1):41–54.

Bhat, C. R. (1998). Accommodating flexible substitution patterns in multi-dimensional choice modeling: formulation and application to travel mode and departure time choice. *Transportation Research Part B: Methodological*, 32(7):455–466.

Bhat, C. R. and Koppelman, F. S. (1999). Activity-based modeling of travel demand. In *Handbook of transportation Science*, pages 35–61. Springer.

Bhat, C. R. and Sardesai, R. (2006). The impact of stop-making and travel time reliability on commute mode choice. *Transportation Research Part B: Methodological*, 40(9):709–730.

Bhat, C. R. and Singh, S. K. (2000). A comprehensive daily activity-travel generation model system for workers. *Transportation Research Part A: Policy and Practice*, 34(1):1–22.

Bowman, J. L. and Ben-Akiva, M. E. (2001). Activity-based disaggregate travel demand model system with activity schedules. *Transportation Research Part A: Policy and Practice*, 35(1):1–28.

Brownstone, D. and Train, K. (1998). Forecasting new product penetration with flexible substitution patterns. *Journal of econometrics*, 89(1):109–129.

Brueckner, J. K. (2002). Airport congestion when carriers have market power. *American Economic Review*, 92(5):1357–1375.

Calvert, R. L. (1985). Robustness of the multidimensional voting model: Candidate motivations, uncertainty, and convergence. *American Journal of Political Science*, 29(1):pp. 69–95.

Felsenthal, D. S. and Machover, M. (2005). Voting power measurement: a story of misreinvention. *Social choice and welfare*, 25(2):485–506.

Gordon, B. R. and Hartmann, W. R. (2013). Advertising effects in presidential elections. *Marketing Science*, 32(1):19–35.

Groseclose, T. (2001). A model of candidate location when one candidate has a valence advantage. *American Journal of Political Science*, 45(4):862–886.

Hensher, D. A. and Reyes, A. J. (2000). Trip chaining as a barrier to the propensity to use public transport. *Transportation*, 27(4):341–361.

Hess, S., Polak, J. W., and Bierlaire, M. (2005). Functional approximations to alternative-specific constants in time-period choice-modelling. In Mahmassani, H., editor, *Transportation and Traffic Theory: Flow, Dynamics and Human Interaction, Proceedings of the 16th International Symposium on Transportation and Traffic Theory*, pages 545–564. Elsevier.

Hess, S., Polak, J. W., Daly, A., and Hyman, G. (2007). Flexible substitution patterns in models of mode and time of day choice: new evidence from the uk and the netherlands. *Transportation*, 34(2):213–238.

Hess, S., Train, K. E., and Polak, J. W. (2006). On the use of a modified latin hypercube sampling (mlhs) method in the estimation of a mixed logit model for vehicle choice. *Transportation Research Part B: Methodological*, 40(2):147–163.

Huber, G. A. and Arceneaux, K. (2007). Identifying the persuasive effects of presidential advertising. *American Journal of Political Science*, 51(4):957–977.

Lam, T. C. and Small, K. A. (2001). The value of time and reliability: measurement from a value pricing experiment. *Transportation Research Part E: Logistics and Transportation Review*, 37(2):231–251.

Litman, T. (2013). Transportation cost and benefit analysis ii. Technical report, Victoria Transport Policy Institute.

Owen, G. (1975). Evaluation of a presidential election game. *The American Political Science Review*, 69(3):947–953.

Owen, G. (2013). *Game theory*. Emerald Group Publishing, fourth edition.

Parry, I. W. and Small, K. A. (2009). Should urban transit subsidies be reduced? *The American Economic Review*, 99(3):700–724.

Peer, S., Knockaert, J., Koster, P., Tseng, Y.-Y., and Verhoef, E. T. (2013). Door-to-door travel times in rp departure time choice models: An approximation method using gps data. *Transportation Research Part B: Methodological*, 58:134–150.

Poole, K. T. (2005). *Spatial models of parliamentary voting*. Cambridge University Press.

Poole, K. T. and Rosenthal, H. (1985). A spatial model for legislative roll call analysis. *American Journal of Political Science*, 29(2):pp. 357–384.

Proost, S. and Dender, K. V. (2008). Optimal urban transport pricing in the presence of congestion, economies of density and costly public funds. *Transportation Research Part A: Policy and Practice*, 42(9):1220–1230.

Rabinowitz, G. and MacDonald, S. E. (1986). The power of the states in u.s. presidential elections. *The American Political Science Review*, 80(1):pp. 65–87.

Revelt, D. and Train, K. (1998). Mixed logit with repeated choices: households' choices of appliance efficiency level. *Review of economics and statistics*, 80(4):647–657.

Rizzi, L. I., Limonado, J. P., and Steimetz, S. S. (2012). The impact of traffic images on travel time valuation in stated-preference choice experiments. *Transportmetrica*, 8(6):427–442.

Roberson, B. (2006). The colonel blotto game. *Economic Theory*, 29(1):1–24.

Schofield, N. (2007). The mean voter theorem: necessary and sufficient conditions for convergent equilibrium. *The Review of Economic Studies*, 74(3):965–980.

Schofield, N., Claassen, C., Gallego, M., and Ozdemir, U. (2011). Empirical and formal models of the united states presidential elections in 2000 and 2004. In *Political Economy of Institutions, Democracy and Voting*, pages 217–258. Springer.

Schrank, D., Eisele, B., Lomax, T., and Bak, J. (2015). Urban mobility scorecard. Technical report, Technical Report August, Texas A&M Transportation Institute and INRIX, Inc.

Small, K. A. (2012). Valuation of travel time. *Economics of transportation*, 1(1):2–14.

Steimetz, S. S. (2008). Defensive driving and the external costs of accidents and travel delays. *Transportation research part B: methodological*, 42(9):703–724.

Sterling, C. W. (1981). Electoral college misrepresentation: a geometric analysis. *Polity*, 13:425–449.

Train, K. (2009). *Discrete choice methods with simulation*. Cambridge university press.

Voorheis, J. (2015). mqtime: A stata tool for calculating travel time and distance using mapquest web services. *Stata journal*, 15(3):845–853.

Walker, J. L., Ben-Akiva, M., and Bolduc, D. (2007). Identification of parameters in normal error component logit-mixture (neclm) models. *Journal of Applied Econometrics*, 22(6):1095–1125.

Wittman, D. (1983). Candidate motivation: A synthesis of alternative theories. *The American political science review*, 77:142–157.

Wittman, D. (1990). Spatial strategies when candidates have policy preferences. In *Advances in the spatial theory of voting*, pages 66–98. Cambridge: CUP.

Ye, X., Pendyala, R. M., and Gottardi, G. (2007). An exploration of the relationship between mode choice and complexity of trip chaining patterns. *Transportation Research Part B: Methodological*, 41(1):96–113.

Young, H. P. (1995). *Equity: in theory and practice*. Princeton University Press.