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The Role of Amenities in the Location Decisions of Ph.D. Recipients in Science and Engineering

Albert Joseph Sumell

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THE ROLE OF AMENITIES IN THE LOCATION DECISIONS OF PH.D. RECIPIENTS IN SCIENCE AND ENGINEERING

BY

ALBERT J. SUMELL

A Dissertation Submitted in Partial Fulfillment
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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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Location-specific amenities have been shown to play an increasingly important role in individual migration decisions. The role certain amenities play in the location decisions of the highly educated may be the cause of persistent regional differences in certain types of human capital, and consequently in regional productivity. This dissertation examines the determinants of the location decisions of new Ph.D. recipients in science and engineering (S&E). A discrete choice random utility model of the city location decisions of new Ph.D.s is developed to estimate .preferences for city attributes as well as willingness to pay for improved amenity quality. By estimating the value Ph.D.s place on various urban amenities, the results of this research help inform policymakers as to their ability (or inability) to attract and retain highly educated workers to their region through public investment in amenity quality.

To link the choice of city with the geographic attributes of cities, a unique micro dataset is used which reports the planned employment city location of S&E Ph.D. recipients in the U.S. at the time of degree. The primary data comes from the 1997-1999 Survey of Earned Doctorates (SED), administered by Science Resources Statistics of the National Science Foundation. The SED is given to all new doctorate recipients in the

U.S. at or near the time of degree, and has a response rate over 90%. The application focuses on approximately 23,000 new Ph.D.s who received their degree in one of twelve S&E fields during the period 1997-1999, and who had made a definite commitment to an employer in a known U.S. metropolitan area.

The results consistently suggest that natural amenities, such as summer or winter temperatures, play a larger role in the location decisions of new S&E Ph.D.s than reproducible amenities, such as crime or air quality. The implication is that policymakers have only a limited ability to improve the composition of their workforce through amenity investment. The results also indicate that the influence of amenities on location choice is related to a number of observable characteristics such as age, race, marital status, citizenship, and Ph.D.s' previous migration behavior.

CHAPTER 1

INTRODUCTION

The economic stability and potential for growth within a region is largely determined by its ability to develop and maintain a highly educated workforce. A specialized cohort of the workforce, new Ph.D.s in science and engineering (S&E), can play a particularly crucial role in the engine of economic growth. Previous literature has suggested that the proportion of the workforce with advanced degrees in science and engineering direct influences the economic productivity within a region (Romer, 1990).

When hired into jobs in industry, new scientists and engineers transmit knowledge acquired in universities to the private sector and create or reinforce networks between industrial and academic scientists (Stephan *et al.*, 2004). Especially important is their ability to transfer tacit knowledge, which cannot be codified and thus requires face to face interaction for transmission. This transmission of knowledge can directly and indirectly enhance the economic position of a city in a number of ways. The knowledge embodied by these workers serves as an input into the production of new scientific discoveries and technological innovations, which can advance the productivity of established businesses or lead to the development of new businesses in an area (Griliches, 1998; Trajtenberg, 1989). When hired into the academic sector, new Ph.D.s contribute to economic growth through their university research and through collaboration with industrial scientists. They also contribute to economic growth by training future scientists and engineers and by enhancing the reputation of the university where they work.

Despite the important role these workers can play in fostering economic growth and development in a region, relatively little is known regarding the individual and geographic factors that influence their location decisions. Understanding these factors is necessary in order for policymakers to identify what policy objectives can be taken to increase the inflow and retention of highly educated scientists and engineers.[1] This dissertation addresses this issue by examining the determinants of the residential location choices of new S&E Ph.D.s at the time of degree. A random utility model (RUM) of migration is employed to estimate how city amenities influence Ph.D.s' utility and their choice of where to work and live. The RUM uses Ph.D.s' observed (utility-maximizing) location choice at the primary metropolitan statistical area (MSA) level to infer how the amenities provided by an MSA affect that probability that it will be chosen.

Given the potential economic gains, municipal policymakers are willing to invest public resources in order to attract and retain more of these workers to their area. However, the ability of policymakers to influence the flow of highly educated workers through public investment in amenities is heavily dependent on the amenity preferences of these workers. For instance, if highly educated workers are primarily drawn to cities that offer superior natural amenities, such as climate or proximity to the coast, then cities without these amenities may need to attract these workers by offering greater financial rewards. Conversely, if these workers are shown to hold strong preferences for

[1]Recent literature has suggested that, due to their high mobility, increasing the number of highly educated workers produced in a region will have a negligible affect on the proportion of a region's workforce that is highly educated (Bound *et al.*, 2001). As a result, in order to improve the composition of the workforce, policymakers are encouraged to invest in attracting highly educated workers produced in other regions, rather than invest in the production of highly educated workers in their own region.

reproducible amenities, such as low crime rates or air quality, then policymakers may effectively attract more highly educated workers by improving the quality of these amenities in cities.

The analysis considers the roles of both site-specific (natural) amenities, and publicly-provided (reproducible) amenities in the location decisions of new Ph.D.s. In doing so, the results can offer insight into the efficacy of policies intended to increase the inflow of highly educated scientists and engineers, and the degree to which cities rich in natural amenities hold an advantage over other cities. In addition, the model considers the influence of Ph.D.s' expected private consumption (income less housing expenditures) in cities, and the proximity of Ph.D.s' current location to alternative cities. By modeling location decisions as a function of expected private consumption and amenity quality, the model can estimate an individual's willingness to tradeoff private consumption for improved amenity quality.

To link the choice of city with the geographic attributes of cities, a unique micro dataset is used which reports the planned employment city location of Ph.D. recipients in the U.S. at the time of degree. The primary data comes from the 1997-1999 Survey of Earned Doctorates (SED), administered by Science Resources Statistics of the National Science Foundation. The SED is given to all new doctorate recipients in the U.S. at or near the time of degree, and has a response rate over 90%. The survey provides information on the degree granting institution, as well as socio-demographic characteristics, field of training, previous work experience, and Ph.D.s postdoctoral plans for employment. In this application, we focus on approximately 23,000 new Ph.D.s who received their degree in one of twelve S&E fields during the period 1997-1999, and who had made a definite commitment to an employer in a known U.S. metropolitan area.[2]

Due to their high mobility at the time of graduation, new Ph.D.s offer researchers a unique view into the migration decision-making process.[3] Previous studies that have examined the determinants of migration behavior have found that amenities play an important role in the decision of where to locate. However, most studies determine the role of amenities in migration by examining the relationship between a region's amenity level and the net or gross migration rates to or from a region. For example, Mueser and Graves (1995) use aggregated migration flow data to calculate migratory elasticities with respect to geographic attributes, and find that a region's climate is an important determinant of its net migration rate.[4] In addition, Gyourko and Tracy (1989) and Clark and Hunter (1992) investigate the roles of taxation and publicly-provided services on inter-city migration flows. These studies have found that violent crime rates, air quality, and student to teacher ratios impact a city's net migration rate and thus can be used to explain wage differentials across regions.

A potential weakness of these studies is that by using aggregated migration data, they can obscure the influence of personal characteristics, such as age or race, on migration choice. The analysis employed here builds upon this research by using individual level data to determine the factors that influence migration decisions. By linking the migration decision with individual characteristics the model estimates how

[2] According to the *Science and Engineering Indicators* (2000), there were approximately 7.7 million employed scientists and engineers in the U.S. in 1997 that were trained in and were working in an S&E field. Approximately 520,000 full-time employed S&E workers held a doctorate degree.
[3] More than 70% of all new S&E Ph.D.s with definite plans during this study period move to a new city after they receive their degree.
[4] Other examples which study the regional determinants of migration flows include Clark and Cosgrove (1991), Graves and Linneman (1979) and Greenwood and Hunt (1989). Similarly, Douglas (1997) and Wall (2001) use net migration flows between regions to infer a region's quality of life.

preference intensities vary according to socio-demographic characteristics, thus offering greater insight into the deterministic relationship between personal characteristics and amenity preferences.

A separate migration literature evaluates the role of amenities on the migration decisions of the highly educated. For instance, Florida (2002a, 2002b) explores the roles of diversity and cultural amenities in attracting young people with a bachelor's degree or above to cities. His work suggests that an area's level of diversity, as measured by the percent of gay households, is a key indicator of its ability to attract a highly educated workforce. According to Florida, a lack of diversity prevents the cultivation of creativity and presents a barrier to attracting talented workers from various ethnicities, races, and sexual orientation. Cities with more diversity can better compete for a wider range of talented workers, and thus can accrue future benefits, economic and otherwise, that result from having a highly skilled workforce.

Although Florida's work has garnered a considerable amount of attention from municipal policymakers, his conclusions have been criticized for using aggregate data and relying on cross-sectional correlations (Krupka, 2004). While evidence suggests that there is a positive correlation between the concentration of highly educated workers and the amount of diversity or cultural amenities in a region, no research has established a causal link between these variables. By estimating the monetary values Ph.D.s place on a host of both traditional and cultural amenities, this research aims to build a more empirically robust case regarding the ability (or inability) of amenity-investment policies to attract highly educated workers to an area.

To estimate the values Ph.D.s place on city attributes, the analysis builds on the random utility model of migration presented in Cragg and Kahn (1997). The authors develop and apply a discrete choice model for estimating the demand for climate. Specifically, they estimate a 48-dimensional conditional logit model which links individual migration decisions across U.S. states to the climate amenities in that state. This approach allows the authors to recover estimates of individuals' willingness to pay for improved climate. The authors point out, however, that the state level analysis is too spatially aggregated to use for valuing local public goods that vary within states. These goods include but are not limited to, crime, school quality, air quality, commute times, and climate indicators that may vary within a state.

Chattopadhyay (2000) also uses a discrete choice model of migration to estimate demand for amenities, but at a smaller geographic level. His research models location choices within a single city (Chicago) to estimate the demand for local public goods such as air quality, school quality, and the demographic composition of cities.[5] By using individual residential choices within a single city, the level of analysis is too narrow to estimate values for amenities that vary across cities. Notably, in order to estimate the values for amenities that vary across cities, such as climate, one would need to model location choices at a national or regional level.

The discrete choice model employed in this dissertation uses individual location decisions at the MSA level *and* on a national scale to estimate the value of amenities. The major advantage of using individual location decisions at an MSA/national level is that the model can estimate values for several important amenities that vary across cities

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[5] Banzhaf and Smith (2003), Palmquist and Israngkura (1999) and Quigley (1985) also use a RUM on individual location decisions within a city to estimate the value of amenities.

(such as general climate), as well as within states (such as crime or air quality), within one framework.

All of the research described above uses migration decisions to infer the amenity preferences of the general population or of the highly educated. It is important to recognize that new S&E Ph.D.s represent a specialized cohort of highly educated workers that engages in a unique labor market. One cannot assume that the amenity preferences of this cohort are equal to those of the general population, or of highly educated workers as they are typically defined (e.g., those with a bachelor's degree). Ph.D.s are different from typical workers in a variety of ways outside of their level of education: they have higher incomes, are less likely to smoke, more likely to vote, and less likely to have children.[6] [7] It is plausible to expect that Ph.D.s not only have different preferences for amenities, but are more informed on and concerned with the quality of amenities prior to choosing a city in which to work and live. In addition, new Ph.D.s are likely to be selective regarding the types of jobs which they are willing to consider, and these jobs may only exist in a few select cities.[8] Thus, while the results provide insight into the amenity preferences of new S&E Ph.D.s, the results cannot be generalized to other attractive cohorts of the workforce such as those with only a college degree in science and engineering.

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[6] For more examples of the dissimilarities across education levels see Baum and Payea (2004).

[7] Although no known previous research has directly examined the empirical relationship between education level and preferences for city amenities, some work has suggested that scientific workers consider different amenities than the rest of the population. For example, Stern (2004) suggests that scientific researchers are willing to accept lower wages in order to work for firms that are more science-oriented. In this respect, the ability engage in scientific discovery is itself an amenity, implying that new Ph.D.s would be willing to sacrifice income in order to live in a more productive environment, or cities with better access to knowledge and/or more research oriented firms.

[8] In other words, new Ph.D.s are unlikely to consider jobs for which non-Ph.D.s are qualified. This point is addressed in more detail in Chapter 2.

The remainder of this dissertation is organized as follows. Chapter 2 reviews the underlying theory of random utility models, and describes the three alternative classes of RUMs estimated in this dissertation: the conditional logit model, the nested logit model, and the mixed logit model. Although each model is based on the same underlying theory, the conditional logit model imposes restrictive utility assumptions that could potentially bias the estimated coefficients. The nested and mixed logit models relax some of the restrictions required by the conditional logit, and may provide more accurate estimates of the influence of amenities on Ph.D. location decisions and their willingness to pay for these amenities.

A key component of all random utility models is the determination of the choice set, which consists of a Ph.D.s' observed city of employment and a set of alternative cities where Ph.D.s were likely to have considered employment. The models estimate Ph.D.s' amenity preferences by comparing the attributes of the observed (utility-maximizing) city of employment to the attributes in alternative (potential) cities. In order to ensure proper estimation of the model, and given the unique nature of the Ph.D. labor market, careful consideration must be paid to the specific set of alternative cities that are included in the choice set. In Chapter 2, a method is developed to determine the set of alternative cities that were most likely to have been considered by Ph.D.s at the time of their job/city selection process.

Chapter 3 provides a summary of the Ph.D.s' included in the empirical analysis from the SED and discusses the data needed to estimate the models. The principal data on Ph.D.s' city choices are identified from the SED. The city location of Ph.D.s going into industry has not been recorded in the SED but has become available to us in verbatim form. Further, because the SED records the academic institution of employment, we are able to determine the city of employment for Ph.D.s employed at an academic institution either as a faculty member or as a postdoctoral appointee. Chapter 3 also describes the migration behavior of new Ph.D.s to and from MSAs, states, and regions of the country. In addition, Chapter 3 discusses the data on MSA attributes which are used to explain location choice in the random utility models.

Chapter 4 describes the estimation of Ph.D.s' expected private consumption. The random utility models arrive at monetary estimates for willingness to pay by identifying the amount of private consumption individuals are willing to forgo in order to live in cities with higher quality amenities. However, because the SED does not ask for Ph.D.s' expected wages or housing expenditures, private consumption must be estimated using alternative data sources. To predict the salary of new Ph.D.s, hedonic wage equations are estimated from a sample of full-time employed Ph.D.s that relate characteristics of an employee, their job, and their location, to their annual salary. The data used to estimate salary comes from the biennial Survey of Doctorate Recipients (SDR), which offers the career information (including annual salary) and demographic information of approximately 30,000 Ph.D.s employed during the same time period. The second component of private consumption, housing expenditures, is estimated using the mean reported housing expenditures of people with similar incomes in each MSA. The data for housing expenditures comes from the 2000 Census 5% Public Use Micro Sample.

Chapter 5 presents the estimation results from the three classes of RUMs. The reliability and robustness of the coefficient estimates are explored by estimating several models with different choice sets and different samples. Furthermore, controls for observable preference heterogeneity are incorporated into the specification, which provides insight into how preferences differ across observable characteristics of the individual. Each model is tested for quality of fit and potential bias and the results are compared with one another in order to determine a set of preferred models to be used in the estimation of willingness to pay.

Chapter 6 uses the estimated utility coefficients from the random utility models to calculate Ph.D.s' willingness to pay for amenity improvements in MSAs. These estimates provide insight into the relative extent to which amenities influence Ph.D. location choice. Chapter 7 concludes by discussing the major policy implications of the results and limitations of the analysis, as well as potential avenues for future research.

CHAPTER 2

RANDOM UTILITY MODELS: THEORY AND METHOD

This chapter describes the estimation methods employed to determine Ph.D.s' preferences for city attributes, and in turn, measures of willingness to pay (WTP) for these attributes. Three classes of random utility models are estimated in this application: the conditional, the nested, and the mixed logit model. All of the models belong to the same larger family of models named generalized extreme value (GEV) models.[9] However, the conditional logit, and to a lesser degree the nested logit, require a property known as the "Independence from Irrelevant Alternatives" (IIA). The mixed logit does not require the IIA property and has become a common approach to discrete choice modeling in recent literature.

This chapter has several components. Section A describes the theoretical framework for determining individual preferences and section B describes the estimation method for the traditional RUM, the conditional logit model.   Sections C and D explain the estimation methods for the more advanced classes of RUMs, the nested and mixed logit models, respectively. Section E explains how the estimated coefficients from each model are used to calculate implicit prices and willingness to pay measures for amenities. Finally, the determination of the choice set, or the set of potential employment cities of Ph.D.s, is discussed in section F.

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[9] The unifying attribute of all GEV models is that the error terms, or unobserved portions of utility, are assumed to follow a generalized extreme value distribution.

A. Random Utility Theory

The construct for the conditional, nested, and mixed logit models all stem from random utility theory. Random utility theory assumes that individuals are able to evaluate the utility level associated with various alternatives, and choose the alternative that offers them the highest utility level. In this application, we assume all Ph.D.s consider an individual specific set of alternative employment cities at the time of degree. Each Ph.D. *i* chooses (is observed in) the job *and* city that maximizes the common random utility function:

$$\max U(Z_j, C_{ij} \mid X_i) \tag{1}$$

subject to:

$$C_{ij} = (1 - T_j)^* [y_{ij}(X_i)] - r_{ij}(y_{ij})] \tag{2}$$

where Z_j is a vector of characteristics in city *j*, C_{ij} is a measure of private consumption for Ph.D. *i* in city *j*, X_i is a vector of characteristics of the individual, and $y_{ij}(X_i)$ and $r_{ij}(y_{ij})$ are the expected annual incomes and housing expenditures for a Ph.D. with attributes X_i in city *j*. Private consumption, C_{ij}, represents the difference between after tax income and housing expenditures.

Substituting the maximal value for C_{ij} yields the indirect utility function:

$$v^*_{ij} = \max_{C_{ij}} U_{ij} = v^*(C^*_{ij}(Z_j, T_j; X_i), Z_j, X_i) \tag{3}$$

Researchers observe the city that yields each individual the highest utility, but do not know the actual utility of each individual. Ph.D.s' utility is comprised of a deterministic component, known to both the researcher and individual, and a random component that represents all aspects of utility that the researcher has not quantified. To express the utility of individual *i* working in city *j*, equation (3) becomes:

$$U_i \text{ (working in city } j) = V_{ij} + e_{ij} \quad (4)$$

where V_{ij} represents the deterministic part of utility, and e_{ij}, represents any non-systematic (unobservable) features of utility. V_{ij} is expressed as:

$$V_{ij} = B'Z_j + \psi C_{ij} + \phi' X_i \quad j = 1,\ldots.., J \quad (5)$$

Where Z_j represents a vector of characteristics ($Z_1, Z_2\ldots.., Z_n$) specific to each city, C_{ij} represents the expected private consumption in city *j* as defined in equation (2), and X_i is a vector of individual characteristics that affect preferences for city attributes, such as marital status or sector of employment. Each individual *i* chooses to work in city *j* if and only if $V_{ij} > V_{ik}$ for all j ≠ k.

The parameter on composite consumption, ψ, represents the utility gained by having another dollar to spend net of housing payments and taxes, or the marginal utility of income. The inclusion of composite consumption in the models allows us to determine a monetary measure of Ph.D.'s willingness to trade-off income for improved amenity quality in cities.

The random utility model requires a number of important assumptions. First, the model assumes that localized public goods vary across MSAs, but are similar within an MSA. This is more realistic for some local public goods, such as climate and amount of recreational space, than for others, such as educational quality and crime indicators. The model also assumes that at the time of degree, each Ph.D. has full information concerning the quality of amenities in their observed MSA and in alternative MSAs. Although restrictive, this is more likely to hold true for MSAs than for census tracts.[10] Finally, the model assumes that non-pecuniary aspects of potential jobs in a sector do not factor into the Ph.D.s decision of where to locate. This is required because we do not have information concerning job specific characteristics of potential jobs available to Ph.D.s in each city.[11]

B. Conditional Logit Model

Under the conditional logit framework, when the individual specific error terms, (e_{i1}, e_{i2}, … e_{iK}), are independently distributed random variables with an extreme value (Gumbel) distribution, the probability that individual *i* chooses city *j* is given by:

$$\text{Prob } (i \text{ chooses city } j) = \frac{e^{v_{ij}}}{\sum_{j=1}^{J} e^{v_{ij}}} = \frac{e^{\beta' Z_j + \Psi C_{ij} + \phi' X_i}}{\sum_{j=1}^{J} e^{\beta' Zj + \Psi C_{ij} + \phi' X_i}} \qquad (6)$$

This is the conditional logit choice probability originally derived by McFadden (1974).[12] The estimated vector of parameters, $\hat{B}$, indicate the effect of city characteristic, *Z*, on the likelihood that a Ph.D. will choose city *j*. Note that the vector of individual characteristics, X_i, does not vary across alternative cities and thus will drop out of equation (6) unless interacted with city attributes.

The basic intuition of equation (6) is that the larger the utility of city *j* as a proportion of the sum of utilities from all cities, the larger is the probability an individual will be observed working in city *j*. By comparing the city-specific attributes in chosen

[10] Even if census tract level data were more theoretically appropriate to use, it would be to empirically formidable to do so on a national scale, given that there are over 50,000 U.S. census tracts.
[11] In other words, the model assumes that a Ph.D. chooses a city employment based on the characteristics of the city and their net income, rather than the non-monetary characteristics of the job.
[12] The conditional logit model includes attributes of the alternatives, such that the regressors differ across alternatives and a single coefficient is estimated for each set of regressors.

cities with the attributes of all cities, the model determines which attributes individuals prefer, or how an increase in the value of an attribute influences individual utility. For instance, if a certain characteristic, such as warmer winters, is more prevalent in chosen cities, the model infers that a warmer winter positively affects choice and is thus preferred to a colder winter, other things constant.

Although the conditional logit model is very practical and useful in many settings, it imposes a restrictive property known as the "Independence from Irrelevant Alternatives" (IIA). The IIA property requires that alternatives share only observed attributes, and no subset of alternatives share unobserved attributes. If the error terms (e_{i1}, e_{i2}, … e_{iK}) share unobserved characteristics across a subset of alternative city choices, the IIA property is violated and the vector of parameters will be biased (Quigley, 1985).

Empirically, the IIA property implies that when an alternative is added (or removed) to a choice set, or the level of an amenity changes in a city, the relative probability of choosing one city over another does not change. There are many situations where this pattern of substitution is unrealistic. For example, if an increase in violent crime in city *A* were to cause a one percent decrease in the probability of moving to city *A*, the IIA property requires that the probability of moving to *all* other cities increases by one percent. If some cities are better substitutes for city *A* than other cities, than this proportionate substitution will not occur and the IIA property will be violated.

As a result of the restrictiveness of the IIA property and the potential bias in the parameters, random utility modelers often employ alternative specifications of the RUM that do not require IIA. The two most common alternatives RUM researchers utilize are the nested logit and the mixed logit model (Parsons & Massey, 2003). A discussion of the nested logit model follows.

C. Nested Logit Model

In order for the IIA property to hold in the conditional logit model, it is implicitly required that individuals perceive all alternatives as equal substitutes. If individuals only consider or systematically prefer one set of alternatives, then some alternatives will be better substitutes for others and IIA will be violated in the conditional logit framework. For example, in recreational demand modeling, it is likely that individuals prefer the alternatives in one region because it's close to their residence, or because alternatives within a region have certain attributes that other alternatives do not have. Thus, individuals will perceive sites in one region as better substitutes for sites in other regions, and the IIA property will not hold when the model groups all alternative sites together.

Generally speaking, if one can determine which subsets of alternatives that individuals are likely to consider as preferred substitutes, then one can maintain IIA in the model by clustering relevant alternatives into subsets, or nests. The nested logit model estimates the probability of choosing a subset of alternatives, in addition to the choice of a specific alternative within a subset. In the example above, an appropriate modeling approach would be to partition sites by region and estimate the probability of choosing a specific region in addition to the probability of choosing a specific site within a region.

In this application, given the nature of the Ph.D. employment market, it is plausible to expect that Ph.D.s prefer a subset of cities within a specific sector of employment over cities in other sectors. Ph.D.s often desire or expect to work in a specific sector of employment before they consider specific jobs (cities) within a sector, and are more likely to consider alternative cities that offer employment in their preferred sector of employment. Thus, the model nests a Ph.D.'s choice of employment sector and employment city.

This model implicitly assumes a two-step decision process. First, a Ph.D. considers whether they will work in industry, an academic full-time (FT) position, an academic postdoctoral fellowship or research associateship (postdoc), or 'other', and second, they search among potential cities that offer employment in that sector.[13] If they decide to work in industry, they choose among one set of available cities, if academe, another set, etc., and the sets may contain different cities. This nesting structure is depicted in Figure 1 below.

The individual's utility employed in sector *k* equals:

$$U_i \text{ (working in sector } k) = V_{ik} + e_{ik} \qquad (7)$$

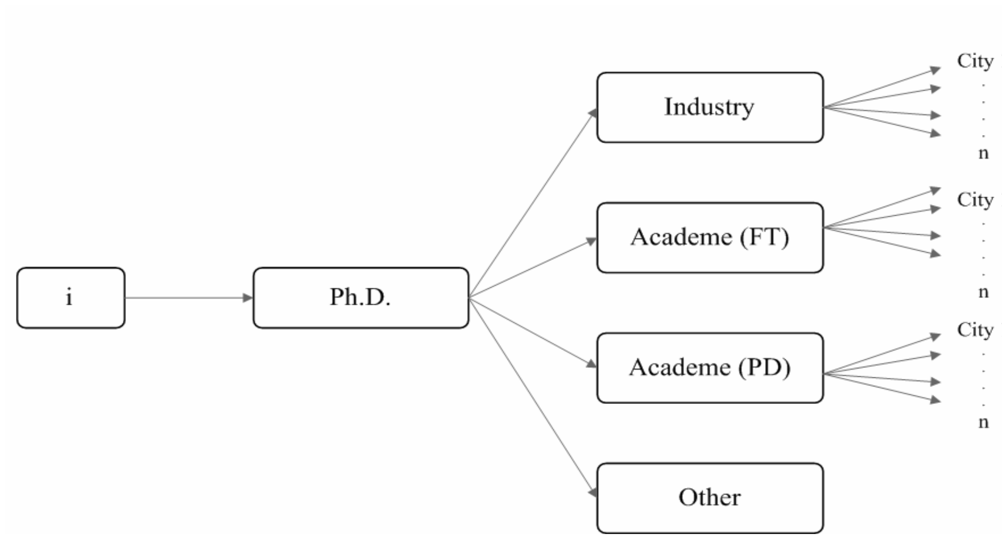
Where V_{ik} and e_{ik} represent the deterministic and random components of utility, respectively. V_{ik} is specified as a function of individual characteristics, X_i, school characteristics, P_s, and the inclusive value for sector *k*, I_i^K, or:

$$V_{ik} = \phi^k X_i + \delta^k P_s + o^k I_i^k \qquad (8)$$

[13]Industry includes all Ph.D.s with definite plans to work in industry or business. Full-time academe includes all Ph.D.s with definite plans for employment in a known 4-year college or university, medical school, or a community college. Postdocs include all Ph.D.s with definite plans to study on a postdoctoral fellowship, or research associateship at a known university. The 'other' sector includes all Ph.D.s with definite plans for employment with the U.S. government, a foreign government, a non-profit organization, an international organization, the military, and self-employed Ph.D.s.

Figure 1:

Choice of Sector then City Nesting Structure



sector, and represent the expected maximum utility associated with choosing a specific sector.[14] Using the vector of coefficients from the city choice conditional logit model, the inclusive values take the following form for each sector:

$$I_i = \ln\left(\sum_{j=1}^{J} e^{\beta\ Zij+\Psi\ C_{ij}+\phi\ X_i}\right) \tag{9}$$

The probability that individual *i* chooses sector *k* equals:

$$P(i, sector\ k) = \frac{e^{\phi^k Xi'+\delta^k P_S+o^k I_i^k}}{\sum_{k=1}^{K} e^{\phi Xi'+\delta P_S+oI_i}} \tag{10}$$

To estimate the city choice and the sector choice jointly, the model combines (6) with (10), as follows. The probability that individual *i* will work in sector *k* in city *j* is given by the product of the probability of *i* choosing sector *k* and *i* choosing city *j*, or:

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[14] The inclusive value is often also referred to as the 'log sum-term' in the literature.

$$P(i, j) = P(i\,j \mid sector\ k) * P(sector\ k) = \left(\frac{e^{\beta Zj + \Psi C_{ij} + \phi X_i}}{\sum_{j=1}^{J} e^{\beta Zj + \Psi C_{ij} + \phi X_i}} \right) * \left(\frac{e^{\phi^k Xi' + \delta^k P_S + o^k I_i^k}}{\sum_{k=1}^{K} e^{\phi Xi' + \delta P_S + o I_i}} \right) \quad (11)$$

The IIA property of the conditional logit model is not exhibited across nests, but is still required within nests. The coefficient on the inclusive value captures the degree of correlation between unobserved components of cities within a sector and provides researchers with a statistical test as to the appropriateness of the model. McFadden (1978) and Ben-Akiva and Lerman (1985) have shown that utility theory requires the coefficient on the inclusive value, $\hat{o}$, to lie between zero and one. Furthermore, the value of the parameter indicates the degree of correlation among alternatives within a nest. The closer $\hat{o}$ is to zero, the greater the degree of correlation among cities within a sector, and the closer $\hat{o}$ is to one, the lower the degree of correlation among cities within a sector. If $\hat{o}$ is greater than one, this implies that cities across nests are more correlated with one another than are cities within a nest. If $\hat{o}$ is less than zero, the implication is that the alternatives within a nest are negatively correlated with one another. When $\hat{o}$ does not lie between zero and one, the model does not satisfy the conditions for consistency with utility maximization (Hauber & Parsons, 2000).

D. The Mixed Logit Model

The mixed logit model (MXL) has become an increasingly feasible and attractive approach to random utility modeling in recent years.[15] The MXL holds two important

[15] The mixed logit model has taken on several names in the literature, although the basic model is the same for each. The following are common alternative names: random parameters logit, random coefficients

advantages over the conditional logit and the nested logit models: it relaxes the IIA property and allows for unobserved individual heterogeneity in preferences. The conditional logit restricts all parameters to be equal for all individuals with the same observed characteristics, while the nested logit requires the parameters to be equal for individuals within the same nest. Thus, these models inherently assume that all individuals with the same observed characteristics hold equal preferences for city attributes. While this may not be a bad assumption for some city attributes, it is unlikely to hold true for all attributes.

The MXL model is a generalization of the standard logit models and controls for unobserved heterogeneity by allowing coefficients to randomly vary across individuals.[16] The coefficients and hence utilities of each individual are correlated with city attributes. By capturing the correlation between individual utility and city attributes, the model allows for a more flexible pattern of substitution. As noted previously, the IIA property is violated in the conditional logit if any subsets of alternatives share unobserved attributes. When correctly specified, the MXL does not exhibit IIA because the individual-specific utilities are correlated with the unobserved attributes of the alternatives.

To understand how the MXL can arrive at more accurate estimates than a standard logit, consider the following example. Imagine a model that includes a city attribute that one group of Ph.D.s prefers, and another group dislike. For example, one group may prefer a large number of art and entertainment (A&E) enterprises, while

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logit, mixed multinomial logit, error components logit, and logit kernel model. For simplicity, we always refer to it as a mixed logit model.

[16] Although the mixed logit controls for unobserved heterogeneity, the model cannot explain the source of heterogeneity (Boxall & Adamowicz, 2002).

another group dislikes the presence of a lot of enterprises because of the associated crowds, noise, etc.[17] The counterbalancing preferences of these groups would likely cancel each other out in the estimation of the choice probability. Thus, the parameter on the number of A&E enterprises in the standard logit model will likely be near zero and statistically insignificant. This result would erroneously suggest that Ph.D.s are generally not concerned with the number of art and entertainment enterprises in their potential city of employment.

In a correctly specified MXL model, the coefficient for A&E enterprises will be positive for one group of Ph.D.s and negative for another group. Although the overall mean may be close to zero, the results from the MXL would not imply that Ph.D.s do not have any preference for the number of A&E enterprises. Rather, and more appropriately, the vector of parameters would suggest that some Ph.D.s have strong preferences for, and others against, a larger amount of A&E enterprises.

Under the MXL, approach the utility of individual *i* observed in city *j* equals:

$$V_{ij} = B_i^{'} Z_{ij} + \psi C_{ij} + \phi' X_i + \varepsilon_{ij} \quad j = 1,....., J \tag{12}$$

Notice the utility of an individual in the mixed logit model is equivalent to the utility equations in the conditional logit (equations 4 and 5), except here the vector of parameters on amenities (B') varies over individuals in the population. In the standard logit, the non-systematic portion of utility is only captured by the error terms (e_{i1}, e_{i2}, … e_{iK}), while in the MXL model, this randomness is captured by a vector of parameters ($B_i^{'}$) in addition to the error terms.

[17] In this example, we assume that the associated crowds, noise, etc. are not separable, or cannot be measured independently of the number of art and entertainment enterprises.

With a known vector of parameters ($B_i^{'}$), the choice probability in the MXL is equivalent to that of the conditional logit. Specifically, the probability that individual *i* is observed in city *j* conditional on $B_i^{'}$ equals:

$$L_{ij}(B_i) = \frac{e^{\beta_i^{'} Z_{ij} + \Psi C_{ij} + \phi' X_i}}{\sum_{j=1}^{J} e^{\beta_i^{'} Z_{ij} + \Psi C_{ij} + \phi' X_i}} \tag{13}$$

The unconditional probability that individual *i* is observed in city *j* equals the integral of $L_{ij}(B_i)$ over all possible values of $B_i^{'}$:

$$P_{ij} = \int \left(\frac{e^{\beta_i Z_{ij} + \Psi C_{ij} + \phi^{'} X_i}}{\sum_{j=1}^{J} e^{\beta_i Z_{ij} + \Psi C_{ij} + \phi^{'} X_i}} \right) f\left(\beta \mid b, \eta\right) d\beta \tag{14}$$

where $f\left(\beta \mid b, \eta\right)$ is a probability density function for β with mean b and standard deviation η. Equation (14) states that the choice probability for an individual is the standard logit probability evaluated at all possible values of β over a given distribution of β over the population. The model reports the weighted mean of β over the population, as well as the derived standard deviation of β across the population (η). The derived standard deviation of β is an estimated parameter that reflects the amount of unobserved heterogeneity in preferences for an attribute(s). Larger values of η signify greater variation in β over the population.

E. Calculating Willingness to Pay

After the random utility models are estimated, the utility coefficients are used to determine the implicit price of an amenity and a Ph.D.s' willingness to pay for an exogenous change to the quality of an amenity. The implicit price (or "part-worth utility") of an amenity equals the change in utility from an additional unit of that amenity, divided by the change in utility from an additional dollar of private consumption (the marginal utility of income). These estimates are calculated using the coefficients from the logit choice probability equations. The implicit price for amenity *z* is defined as the coefficient on amenity *z* over the coefficient on composite consumption, or:

$$P_z = \left(\frac{\partial V / \partial Z}{\partial V / \partial C} \right) = \left(\frac{\hat{\beta}_z}{\hat{\psi}} \right) \tag{15}$$

where $\hat{\beta}_z$ is the coefficient on amenity *z* and $\hat{\psi}$ is the coefficient on composite consumption. While P_z tells us the amount Ph.D.s are willing to pay for a marginal increase in amenities, it is also of interest to estimate the amount Ph.D.s are willing to pay for non-marginal increases in the value of amenities. Determining willingness to pay is equivalent to estimating welfare changes (compensating variation) that result from changes to amenity quality in cities. The intuitive interpretation of a welfare change is as follows. If amenity quality in cities decreases (increases) by some exogenous amount, how much does an individual's composite consumption have to increase (decrease) in order to keep their utility the same?

The general formula used to calculate willingness to pay is the same for the conditional, nested, and mixed logit models.

$$WTP_i = [EU_i^1 - EU_i^0] / \hat{\psi} \tag{16}$$

where EU_i^0 represents the expected maximum utility for individual *i* before any change in amenity quality, and EU_i^1 represents the expected maximum utility following the amenity change, and $\hat{\psi}$ represents the marginal utility of income. Because the marginal utility of income is constant (equal to the coefficient on private consumption), income effects are zero. This implies that the amount someone is willing to pay for an increase in the quantity of amenity *z* equals the amount they are willing to accept for a decrease of the same quantity.[18]

Using the coefficients from the conditional logit models, the expected maximum utility is estimated as:

$$EU_i^A = ln\sum_{j=1}^{J}\{\exp(\hat{B}'Z_j + \hat{\psi}C_{ij} + \hat{\phi}'X_i)\} \tag{17}$$

where *A* equals 0 or 1, which reflects the expected maximum utility with and without the change in the level of amenity quality in all cities, respectively.

The expected maximum utility in the nested logit differs for Ph.D.s in different sectors. For individuals in sector *k*, expected utility takes the form:

$$EU_i^A = ln\sum_{j=1}^{J}\{\exp(\hat{\phi}^k X_i + \hat{\delta}^k P_s + \hat{o}^k \hat{I}_i^k)\} \tag{18}$$

where $\hat{I}_i^k = \ln\left(\sum_{j=1}^{J} e^{\hat{\beta} Z_{ij} + \hat{\Psi} C_{ij} + \hat{\phi} X_i}\right)$ and *A* reflects the expected maximum utility with and without the amenity change.

Finally, in the mixed logit model, the expected maximum utility is differs for all individuals in sample, depending on the variation in β. For individual *i*, the expected utility level equals:

[18] In other words, the compensating variation equals the equivalent variation.

$$EU_i^A = ln\sum_{j=1}^{J}\{\exp(\hat{B}_i^{'}Z_j + \hat{\psi}C_{ij} + \hat{\phi}'X_i)\} \qquad (19)$$

where *A* reflects the expected maximum utility with and without the amenity change. Note that the WTP estimates for attributes with random coefficients must accommodate the distribution of estimates across the population. Because $\hat{B}_i^{'}$ is unobserved for each individual, the variations in $\hat{B}_i^{'}$ are simulated randomly according to the specified distribution around the mean value of the coefficient. For example, assume attribute *x* has an estimated mean coefficient $(\overline{B}_X)$ and derived standard deviation $(\hat{\eta})$. To estimate WTP for a change in the level of attribute, first we estimate random coefficient values for each individual as ($\overline{B}_X$ + $\hat{\eta}$ * u), where (u) represents random deviates. This random coefficient value enters the expected utility equation for the mixed logit (equation 19), after which WTP is calculated as defined in equation (16).

F. Determination of the Choice Set

The models described above estimate utility coefficients by comparing the attributes of the observed city of employment which offers the Ph.D. the highest utility level, to the attributes in alternative cities of employment, or cities where a Ph.D. may have considered residing but decided against it. Two major issues must be addressed before the random utility models can be estimated. First, we must establish the choice set for each Ph.D., or determine the relevant set of alternative cities Ph.D.s were likely to have considered while conducting their job search. Second, we must establish the covariates, or the relevant set city characteristics that were likely to have influenced the Ph.D.’s choice of city among the alternative cities in the choice set. This section describes the criteria used to determine the individual's choice set. The relevant set of city attributes assigned to each city will be discussed in Chapter 3.

Incorrect specifications of the choice set can lead to biased utility coefficients and resulting WTP estimates (Phaneuf & Herriges, 1999). As a result, careful consideration must be paid to the specific set of alternative cities that are selected into the choice set. The formation of the choice set requires two implicit assumptions. First, to estimate the model, the choice set must be greater than one, which requires us to assume that all Ph.D.s could have found employment in a city other than their observed city.[19] Second, all alternative cities assigned to the choice set are assumed to have a positive (non-zero) probability of being the selected city (McFadden, 1978). In other words, the models require that Ph.D.s are not observed in a potential city because that city offered them lower utility, not because they were not able to locate in that city.[20]

Previous researchers have devised a number of criteria to assign alternatives to the choice set. The most common approach is to assign all possible alternatives to the choice set, which implicitly assumes that all possible alternatives are considered by each individual (Hicks & Strand, 2000). The 'complete alternatives' approach is not appropriate for the purposes of this application due to the fact that there over 300 MSAs in the U.S., and the dimensionality of estimation would become exponentially large if all alternatives were included in the choice sets.

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[19] Another way of stating this assumption is that the choice probability defined in equation (6) is assumed to be less than one.

[20] Note that this assumption does not require that individuals actually consider all alternatives included in their choice set. When the scope of the choice set is larger than the set of alternatives that were actually considered the model will arrive at accurate estimates, conditional on satisfying the independence from irrelevant alternatives assumption (Ben-Akiva & Lerman, 1985).

When dealing with a large number of alternatives, a common approach is to randomly select a limited number of alternatives into the choice set (Blackley & Ondrich, 1988; Ioannides & Zabel, 2002). McFadden (1978) has shown that this approach will provide consistent and efficient estimates when all alternatives in the assigned set have a positive probability of being the observed choice. This approach is not theoretically appropriate for the purposes of this application because it would require us to assume that all Ph.D.s could have found adequate employment in any city.

The primary goals of the choice set selection process is to determine the alternative cities that were most likely to have actually been considered by each Ph.D., and to eliminate cities in which Ph.D.s could not have found adequate employment. In order to accomplish these goals, we weight the probability that any city will be selected into a Ph.D.'s choice set. The process of changing the probability that certain cities are included in a choice set has been termed 'importance sampling' (Ben-Akiva & Lerman, 1985). A considerable number of studies have examined the affect of using a full choice set approach, a random sampling approach, or an importance sampling approach to selecting alternatives into a choice set. For example, Haab & Hicks (1997) use the attributes of individuals and alternative sites to estimate the probability that an alternative will appear in an individual's choice set. By interacting individual attributes with alternative specific attributes, the authors eliminate the number of irrelevant sites that can enter into the choice set. The authors conclude that their approach provides more precise estimates than RUMs that use a randomly selected or complete choice set. Other studies of recreational demand, such as Parsons and Kealy (1992), Hauber and Parsons (2000), and Hicks and Strand (2000), have used the geographic proximity of sites from an individual's residence to determine the relevant set of alternatives.

The process of choice set determination is particularly complicated for the purposes of this model due to the complexity and uniqueness of the Ph.D. labor market. For one, new Ph.D.s, eager to obtain returns to their investment in graduate school, are unlikely to consider or accept jobs for which non-Ph.D.s are qualified. For instance, a Ph.D. in mechanical engineering who wishes to go to Yuma, Arizona, may find that there are no firms in, or near, Yuma that are willing to hire mechanical engineering Ph.D.s. In addition, new Ph.D.s typically will limit their job search to a specific sector, either as a result of individual preferences or because of job market considerations. For example, a Ph.D. in mathematics who is qualified for a number of industrial jobs may not search for these jobs because she desires to work in academe. Alternatively, a biologist who desires to work in academe will likely limit their search to postdoctoral appointments because he is unlikely to be hired in a tenure track position at an academic institution.[21]

The approach used to select alternative cities is closely related with the method used by Feather (1994). In a RUM application to lake recreation, Feather uses the observed visitation rates of lakes to assign probabilities that any lake will appear in an individual's choice set. He contends that the more popular a lake, the more likely that an individual considered going to that lake. Therefore, popular lakes should have a higher probability of appearing in an individual's choice set than other lakes, and lakes which no

[21] Stephan and Ma (2004) find that the probability a new Ph.D. accepts a postdoctoral position is positively related to the supply of new Ph.D.s and negatively related to the demand for new Ph.D.s in academe. In addition, one in eight respondents from a 1995 survey reported that they accepted their most recent postdoc because other jobs were not available. This implies that the postdoc sector is often not the top sector choice of new Ph.D.s, or that new Ph.D.s may be willing to accept a faculty position in a city with worse amenities over a postdoctoral position in a city with better amenities.

one attends should not be included in any individual's choice set. In comparing this method to the random sampling procedure, Feather notes that the models that used importance sampling to generate the choice sets had welfare estimates that were significantly more stable with respect to the number of alternatives than the random sampling method.

In this application, the probability that a city is selected into a Ph.D.'s choice set is weighted based on the popularity of that city among Ph.D.'s who were likely to be competing for the same jobs. The rationale for this approach is that the greater the proportion of Ph.D.s in the same job market (job market set *c*) that are observed in city *k*, the more likely that a Ph.D. in job market set *c* considered employment in city *k*. Therefore, city *k* should have a larger probability of being selected into the choice set of all Ph.D.s job market set *c*. Similarly, if no Ph.D. in job market set *d* was hired in city *j*, we assume that city *j* did not have an adequate job opportunity for any Ph.D. in job market set *d*.[22] Therefore, city *j* is eliminated and has no possibility of being in the choice set for any Ph.D. in job market set *d*.

The job market sets are identified according to a Ph.D.'s field of training and her sector of employment.[23] The implicit assumption here is that Ph.D.s only compete for jobs with other Ph.D.s in their field of training and their sector of employment.[24] For

[22] The Survey of Earned Doctorates is given to everyone granted a Ph.D. in the U.S., and has over a 90% response rate. Our data covers all Ph.D.s that made a definite commitment to an employer in a U.S. MSA. Thus, we assume that if no Ph.D. is observed in a city, it is because no job was available to any Ph.D. in that job market set, not because a job was available in that city but no Ph.D. was willing to accept it.

[23] Doctorate degrees were granted in a total of 166 detailed science and engineering fields. We group detailed fields into 15 broad fields matching how the Information Sciences Institute (ISI) categorizes journals in science and engineering.

[24] We initially considered defining job market sets according to the year the Ph.D. graduated as well. We found that cities that offer employment to Ph.D.s in a specific field remained relatively constant over the three years of our data. Therefore, we do not expect the choice sets (and results) to significantly vary

instance, assuming a Ph.D. trained in biology is not competing for the same types of jobs as a Ph.D. trained in astronomy, the city choice of an astronomer does not inform us as to the potential city choices of a biologist, and vice versa.[25] In addition, we assume Ph.D.s who choose to work industry are not considering the same set of jobs as Ph.D.s who choose to work in academe, or that Ph.D.s prefer employment in a specific sector.[26] Overall, there are 45 job market sets (15 fields* 3 sectors), with each job market set containing Ph.D.s in the same field and sector of employment.

The probability that an alternative city is selected into the choice set of a Ph.D. is directly proportional to the percent of Ph.D.s in her job market that located in that city. Specifically, if 25% of all Ph.D.s in a job market set locate in New York City (NYC), then NYC has a 25% probability of being selected into the choice set of all Ph.D.s in that job market set for each draw. Cities are selected into the choice set using *K* draws without replacement from a list of all observed cities in each job market set. Thus, for each Ph.D. in job market *c*, city *j* has a selection probability in draw X equal to:

$$P_{c,j} = \left[{(n_{c,j} - X)}\big/{(N_C - X)} \right] \tag{20}$$

where $n_{c,j}$ is the number of Ph.D.s observed in city *j* from job market set *c*, and N_C is the total number of Ph.D.s in job market set *c*. Finally, each Ph.D.'s observed city choice is added to the choice set and all duplicate cities are deleted. Thus, after *K* draws each

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depending on whether job market sets are identified by time periods. The effect of using time windows in importance sampling was examined by Banzhaf and Smith (2003).

[25] The assumption that S&E Ph.D.s primarily search for jobs in their own field is supported by surveys of employed S&E Ph.D.s. Specifically, the 2000 National Science Foundation's Science and Engineering Indicators reports that 95.5% of employed Ph.D.s in S&E accepted a position that was closely or somewhat related to their field of training.

[26] No question is asked in the SED that allows researchers to differentiate between Ph.D.s who consider jobs in only sector and Ph.D.s who consider jobs in multiple sectors. However, Ph.D.s' sector choice is heavily dependent on field of training. This is illustrated in Table A.1 in the appendix, which reports Ph.D.'s choice of sector by field of training.

Ph.D.'s choice set varies from a minimum of two alternatives to a maximum of (K+1) alternatives.

The random utility models will be estimated with different sized choice sets. Specifically, the number of draws (K) varies from five to twenty five for each random utility model.[27] There is no basis *a priori* to prefer one choice set size to another. Theoretically, the models estimated with smaller choice sets may have biased coefficients if the choice sets systematically exclude relevant alternatives (cities that were likely to be considered by Ph.D.s). Conversely, the models estimated with larger choice sets may have biased coefficients if the choice sets systematically include cities in which Ph.D.s would not have been able to find adequate employment.

[27] We start with the five draws because this is the minimum number of draws Parsons and Kealy (1992) suggest are necessary to obtain reliable results when dealing with a large number of alternatives.

CHAPTER 3

DATA AND DESCRIPTIVE STATISTICS

This chapter describes the data used to estimate the random utility models. Each model requires data on Ph.D.s' city choices as well as attributes from U.S. metropolitan areas. The data on Ph.D.s' city choices comes from the Survey of Earned Doctorates (SED), administered by Science Resources Statistics of the National Science Foundation. The SED is a census of all newly minted Ph.D.s in the U.S. and is administered at or near the time of degree, and has a response rate of approximately 92%. The analysis is restricted to all Ph.D.s in a science and engineering field from fiscal years (FY) 1997-1999 with definite plans for employment in a U.S. MSA. Section A provides an overview of Ph.D.s in the SED and discusses our ability to draw inferences regarding the preferences of the science and engineering workforce from this data. Section B examines the migration behavior of these Ph.D.s, and explores the ability of metropolitan and states to retain Ph.D.s from the area and/or attract Ph.D.s produced in other regions. Section C describes the MSA level attributes included in the random utility models.

A. Ph.D.s in the Survey of Earned Doctorates

Table 1 presents the distribution of new Ph.D.s that completed the survey between FY 1997 - 1999 by sector of employment. As indicated by Table 1, 65,427 new S&E doctorates completed the survey between FY 1997-1999, but only 25,827 of these Ph.D.s have a known U.S. employment city. There are three noteworthy reasons the U.S. city of employment is not observed for all new S&E Ph.D.s. First, 36.3% of all new S&E Ph.D.s did not name an employer or an employment location on their survey because they had not made a definite commitment to an employer at the time the survey was administered.[28] Secondly, 10.2% of S&E Ph.D.s with definite plans made a commitment to an employer outside the U.S. such that the location choice is not germane to the analysis. Finally, approximately 31% of S&E Ph.D.s with definite plans in the U.S. either do not report their employment/city or their employment city is not accessible to researchers. This last point warrants further explanation. While the SED asks all graduates to identify the geographic location of their employer, the SED data available to researchers only identifies the employment state or foreign country of Ph.D.s.[29] We are able to identify the city location choices of industrial Ph.D.s through a verbatim file that has become available to researchers since 1997.[30] In addition, the city choices of Ph.D.s employed at a known academic institution are identified by matching the institution with its geographic location.[31] However, the employment city of Ph.D.s not employed in industry or at a known academic institution cannot be determined from the data. The empirical analysis is thus restricted to S&E Ph.D.s who had accepted and reported a

[28] Ph.D.s with definite plans had either signed a contract or made definite commitment to a new employer, or were returning to or continuing in pre-doctoral employment.
[29] Specifically, the SED asks all Ph.D. recipients to "name the organization and geographic location where you will work or study."
[30] This verbatim file has only been available to researchers since 1997. As part of a larger project, we also coded the data by firm name. See Stephan *et al.* (2004) for more information on this project.
[31] 683 new faculty appointments and 6,213 postdoctoral appointments in the U.S. did not report a legible academic institution on their survey. A large proportion of postdoctoral appointments that did not report an academic institution likely accepted a postdoctoral position in another sector, such as at an industrial lab or with a government agency. Stephan and Ma (2004) report that between 1981 and 1995, 30% of new postdoctoral appointees with definite plans accepted a position in a sector outside of academe.

position with an industrial firm or an academic institution at the time they completed the survey.

An important issue to investigate is whether the inferences drawn from the empirical analysis can be generalized to the entire population of S&E Ph.D.s, or to the population of new S&E Ph.D.s.[32] First we will address whether the estimated preferences of new Ph.D.s can be generalized to the population of all employed S&E Ph.D.s. As shown in Table 1, slightly more than 45% of new S&E Ph.D.s with definite plans during this study period have plans to work in a postdoctoral position, while 25% have plans to work in industry and only 14% have plans to work in academe. Because postdocs eventually transition into more permanent employment positions in either industry or academe, a representative sample of experienced workers will have a substantially smaller proportion of postdocs in comparison. As a whole, faculty comprise 44% of the entire doctoral S&E workforce, 38% of S&E Ph.D.s work for a private firm, and postdoctoral appointees comprise approximately 6% of the doctoral S&E workforce.[33]

The types of job opportunities that are available to new Ph.D.s have changed considerably over the past thirty years. In particular, there has been a dramatic decrease in the share of new Ph.D.s who immediately find employment in a faculty position at an academic institution, and in turn, a proportional increase in the share of postdoctoral

[32]The empirical analysis only includes Ph.D.s with definite plans and a known city of employment. The population of new S&E Ph.D.s includes Ph.D.s without definite plans for employment and Ph.D.s without a known city. The population of S&E Ph.D.s includes all employed doctorates, regardless of the time they earned their degree.

[33] Source: *Characteristics of the Doctoral Scientists and Engineers in the U.S.* (1997). National Science Foundation/Division of Science and Resource Studies.

appointments.[34] Ehrenberg (1992) notes that the total share of new S&E doctorates starting a postdoctoral appointment increased from 22% to 39% between 1970 and 1988, and in turn the proportion of new faculty decreased from 44% to 24% over the same time period.[35]

Of critical importance for the purposes of this analysis is not the type of employment new Ph.D.s find, but how their employment opportunities may influence their city choices. Prior to selecting between alternative jobs/cities, Ph.D.s will weigh both the characteristics of each job (salary, workload, ability to engage in research, etc.) in addition to characteristics of the surrounding city. Employment characteristics constant, an individual will select the city with the bundle of amenities that best matches her preferences. However, the job related characteristics are likely to hold greater importance for newly minted Ph.D.s, particularly postdocs, than they would for experienced Ph.D.s. First, a postdoc is likely to be more willing to endure an appointment in a city with low quality amenities simply because the appointment is naturally short-term.[36] In addition, as with the choice of a graduate school, a postdoctoral appointment influences an individual's future employment prospects. Regardless of the location, higher quality appointments (those with a highly respected mentor, at higher

[34] A Ph.D.'s choice of sector is largely determined by their field of training. This is illustrated in Table A.1 of the appendix, which reports the number and share of new doctorates with definite plans going into each of the four sectors for ten broad S&E fields. The postdoc sector represents the dominant sector choice among the majority of S&E disciplines. Notably, approximately three in four biologists and astronomers, and more than half of all chemists and physicists accept a postdoctoral appointment before moving on to more permanent employment in another sector. Industry is the most popular sector destination for engineers and computer scientists, while mathematicians are most likely to find employment in an academic institution.

[35] This trend can be attributed to a number of potential factors. The decrease in the share of new faculty may be a byproduct of a tightening of the academic labor market, caused by proportionally larger increases in the supply of new doctorates relative to the number of newly available tenure track positions in academic institutions (Ehrenberg, 1999). Alternatively, the increased share of postdocs may simply reflect that a longer training period is required before a Ph.D. can obtain a faculty appointment (Ehrenberg, 1992).

[36] Stephan and Ma (2004) report that in 1990 the median length of a Ph.D.'s postdoctoral experience was 34 months.

ranked institutions, with greater opportunities to publish in scientific journals, etc.) are more likely to be selected by new Ph.D.s because it will enhance their ability to select a higher quality job/city after the appointment is complete.[37]

The stakes are somewhat different for industrial placements and Ph.D.s going into academe. City attributes are likely to weigh more heavily into the decision of where to work because the duration of their residency in the city is expected to be longer.[38] More generally, individuals will be less willing to tolerate low quality amenities when choosing between potentially long-term career positions than when choosing between short-term postdoctoral positions. To account for the potential influence of the expected employment duration on the estimated amenity values, the empirical models introduce controls which relate the estimates to Ph.D.s' sector of employment.

Still in question is whether the subpopulation of new Ph.D.s included in the empirical analysis is a random sample of all new S&E Ph.D.s. In particular, sample selection bias may result from the exclusion of Ph.D.s without definite plans as well as the exclusion of Ph.D.s who do not report their employment city. Table A.2 of the appendix offers some insight into the potential existence of selection bias by showing the individual and institutional characteristics of Ph.D.s included in the empirical analysis (Ph.D.s with definite plans in the U.S. and with a known academic institution) vs. Ph.D.s

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[37] This is not to suggest that city amenities do not have any influence on the choice of a postdoctoral position, just that city amenities are likely to matter less for new Ph.D.s choosing between postdoctoral positions than for new Ph.D.s choosing between more permanent positions.

[38] As with postdocs, the potential for future employment elsewhere may influence the decision of where to work for new Ph.D.s in industry and new faculty. These Ph.D.s also face high turnover rates during their first few years of employment. For example, Ehrenberg (1992) reports that 15% of non-tenured professors employed in the U.S. are not employed in the same institution in the next year. In addition, Bender and Heywood (2005) find that approximately 22% of S&E Ph.D.s employed in a nonacademic institution changed employers within a two year period.

that are not included in the empirical analysis (Ph.D.s without definite plans in the U.S. and Ph.D.s that did not report an academic institution).

Although some notable differences exist, the samples are reasonably similar regarding the observable characteristics of Ph.D.s. Compared to Ph.D.s without definite plans, the sample of Ph.D.s with definite plans has a larger proportion of males (68% vs. 62%), U.S. citizens (67% vs. 61%), and white Ph.D.s (65% vs. 58%). As expected, whether or not a Ph.D. has definite plans is heavily influenced by her employment status prior to graduation. In particular, Ph.D.s who were full-time employed one year prior to graduation comprise approximately 25% of the sample of Ph.D.s with definite plans, compared to only 12.5% of the sample of Ph.D.s without definite plans. Institutional characteristics also play a role in determining post-graduation employment status. The sample of Ph.D.s with definite plans has a higher proportion of Ph.D.s from top 110 institutions (81%), compared to Ph.D.s without definite plans (76%). In addition, Ph.D.s from top-ranked institutions comprise approximately 65% of the sample of Ph.D.s with definite plans, compared to 59% of the sample of Ph.D.s without definite plans.[39]

The last two columns of Table A.2 compare the characteristics of Ph.D.s with definite plans and a known academic institution to the characteristics Ph.D.s with definite plans but an unknown academic institution. The sample of Ph.D.s who report their academic institution is very similar in terms of observable characteristics to the sample of Ph.D.s who do not report an academic institution. In fact, the difference between sample means does not exceed six percentage points for any single characteristic.[40] These

[39] A chi-square test that these characteristics are equal across samples can be rejected the 1% level of significance.

[40] The largest difference between these samples is in the proportion of biologists. Specifically, biologists comprise approximately 37% of the sample of Ph.D.s with an unknown academic institution, compared to

considerations suggest that it is reasonable to draw inferences from the analysis for new Ph.D.s with definite plans, regardless of whether they reported their academic institution of employment. However, more sizeable differences exist between the samples of Ph.D.s with definite plans and Ph.D.s without definite plans. In particular, females, non-whites, and non-citizens are somewhat under-represented, while new Ph.D.s who were full-time employed prior to graduation and from top ranked research universities are somewhat over-represented in the empirical analysis.

B. Migration Behavior of New Ph.D.s

Local policymakers have a vested interest in the migration behavior of highly skilled workers. The presence of a highly skilled workforce can be a magnet for new businesses and local metropolitan areas can receive substantial gains in productivity as a direct result of the contributions of nearby graduates (Link, 1995). A few examples include Stanford's role in the creation of Silicon Valley, M.I.T. and Harvard's role in Route 128, and the role of Duke University, UNC Chapel Hill, and NC State in the development of Research Triangle Park.

While it is the local areas that can receive the largest benefits from universities, it is the state that bears the burden of funding these universities. As a result, state policymakers are especially concerned with the returns on their investments in universities, and may relate this concern to the number of highly skilled workers that migrate out of state after receiving their degree. Examining the migration behavior of Ph.D.s from states and metropolitan areas not only provides insight to the extent to which

43% of the sample of Ph.D.s without a known academic institution. A chi-square test that these percentages are equal across samples can be rejected at the 1% level of significance.

knowledge created at local universities is absorbed by the local economy, but also the amount by which states recoup their substantial investments in higher education.

With this in mind, Table 2 shows the inter-state and inter-regional migration patterns of new S&E Ph.D.s. To measure the net gains or losses of new S&E Ph.D.s in an area, the table compares the number of Ph.D.s with definite plans trained in each state and region, to the number with definite plans for employment in each state and region. Table 2 indicates that 11% more Ph.D.s are trained in the U.S. than are employed in the U.S. during the study period. This is because the number trained includes Ph.D.s with definite plans for employment in a foreign country.[41] Of Ph.D.s employed in the U.S., slightly less than half are employed in the same region in which they were trained, and only 37% are employed in the same state where trained.

As indicated by Table 2, there is a lot of variation between states and regions in terms of net gains or losses. Notably, there is a general migration of Ph.D.s away from the central states toward the coast. Nine of the nineteen coastal states employ more new Ph.D.s than they train, compared to only six of the thirty-one states that do not lie on the coast. Only two regions, New England and the Pacific, employ more Ph.D.s than they train. The Pacific region fares the best, largely due to the remarkable role of California, which retains a higher percentage of Ph.D.s and imports more Ph.D.s than any other state in the nation. The boom in information technology during the study period, which was particularly strong in California, Oregon, and Washington, undoubtedly contributes the robust gains of the Pacific region.

[41] We do not have any information regarding the number of Ph.D.s trained in foreign nations that migrated to the U.S. during these years. Thus, if taken alone, the table overestimates the net loss of Ph.D.s in each state and to the U.S. as a whole.

Table 2 also shows that there is a remarkable "brain drain" from the central regions during the sample period. The nine states in the East Central regions are major net exporters of Ph.D.s. Only about one in four Ph.D.s trained in the East Central region finds employment in their state of training on average, and each state suffers a net loss in excess of 14%. The pull from the East North Central region is particularly severe. Overall, the region suffers a net loss of 2,655 Ph.D.s, more than three times the amount lost from any other region. When the fifty states are ranked in terms of net gains and losses, where the top net gainer is ranked 1st and the largest net loser is ranked 50th, East North Central states: Michigan, Wisconsin, Indiana, Ohio, and Illinois, respectively rank 44th, 45th, 47th, 48th and 49th.[42] States in the West Central regions generally do not fare much better; of the eleven states, all but South Dakota and Arkansas employ fewer Ph.D.s than they produce.

Table 3 takes a more detailed look at the migration behavior of new by Ph.D.s by examining the ability of metropolitan areas to retain and attract new Ph.D.s. The table ranks the top 25 MSAs according to the number of new Ph.D.s employed and produced in each MSA. A number of striking stories arise. On average, an MSA retains approximately one of every five Ph.D.s that they train. Despite the high mobility of new Ph.D.s, it is evident from Table 3 that areas that produce more Ph.D.s generally employ more Ph.D.s as well. Of the top 25 producing MSAs, eighteen are also in the top 25 in terms of employment of new Ph.D.s. As a whole, the top 25 producing MSAs, which represent approximately 35% of the U.S. population, employ more than half of all new Ph.D.s with definite plans in the data.

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[42] Surprisingly, New York state ranks 50th, or it loses more Ph.D.s on net than any other state. This is largely due to the role of bordering New Jersey, which employs about one of four Ph.D.s trained in New York.

The ability of metropolitan areas to retain locally trained Ph.D.s and attract them from other areas varies substantially. For instance, Los Angeles, San Jose, and Chicago each retain more than 25% of the Ph.D.s produced locally, compared to Champaign-Urbana, IL and Lafayette, IN which only employ approximately 10% of the Ph.D.s they train. In addition, the number of Ph.D.s trained in Champaign-Urbana, IL and Lafayette, IN combined is slightly greater than the total number trained in Los Angeles (1,468 vs. 1,374). Yet, Los Angeles employs more than triple the amount of Ph.D.s employed in Champaign-Urbana and Lafayette combined (883 vs. 279). These variations demonstrate that the presence of a large university, by itself, does not guarantee sufficient job opportunities to attract a large number of Ph.D.s. Certainly, other factors, such as a large industrial sector and/or high quality amenities, are important in determining the ability of MSAs to attract or retain new Ph.D.s.

Although we do not investigate the precise role of amenities in the location decisions of new Ph.D.s in this chapter, Table 3 provides some casual evidence that new Ph.D.s are attracted to areas with higher quality amenities. For instance, thirteen of the top 25 U.S. MSAs from the *Places Rated Almanac* (Savageau & D'Agostino, 1999) rankings are also in the top 25 in terms of employment of new Ph.D.s.[43] This relationship between rankings extends beyond the top 25 MSAs. More than half of the top 100 MSAs from the PRA are one of the top 100 chosen MSAs of new Ph.D.s. In addition, the overall correlation coefficient between the *Places Rated Almanac* rankings for all U.S. MSAs, and the MSA rankings in terms of employment of new Ph.D.s, is a robust 0.714.

[43] The *Places Rated Almanac* Rankings are based on the mean of an index that combines each area's quality of climate, crime, transportation, education, the arts, health care, and recreation.

C. MSA Data

To recreate the information available to Ph.D.s at the time of degree, the random utility model includes twenty eight MSA-level variables, Ph.D.s' expected composite consumption, and the distance in miles between Ph.D.s' MSA of training and all alternative MSAs in their choice set. The variable distance is expected to play a significant role in location choice because it captures both the explicit monetary costs and the non-pecuniary costs of moving.[44]

Table 4 defines and presents summary statistics for all of the MSA variables included in the models.[45] Each MSA variable is placed into one of four broad categories: natural amenities, publicly-provided amenities, "other" city characteristics, and region of the country. Natural amenities are 'pure' public goods of an MSA, or environmental attributes which are non-purchased and non-alterable. These include January and July temperatures, July relative humidity, hours of January sunlight, the percent of an MSA's surface area covered by water, and a dummy variable indicating whether the MSA lies on the coastline.

Publicly-provided amenities are reproducible public goods which can be altered through public investment. These include crime rates, per-student expenditures and pupil to teacher ratios in public schools, acres of state or national protected parkland, number of bad air quality days, number of art and entertainment enterprises, number of superfund sites, and the average commute time to work. The "other" category includes all city

[44] Note that distance and composite consumption are the only characteristics that vary between both individuals and alternatives in the choice set. To calculate the distance in miles between the city of training and city of employment, we first gathered the latitude and longitude coordinates of the institution where the Ph.D. was trained and where they were employed. After converting the coordinate measures from degrees to radians, we multiply the number of degrees per radian by the number of miles per degree on a sphere the size of the earth. Distance equals one if the alternative MSA is the same as the MSA of training.

[45] See Table A.3 in the appendix for source information of MSA data.

characteristics that are neither natural nor reproducible amenities, but are likely to influence a Ph.D.'s location decision. In general, policymakers have little ability to influence the amount of these goods in their MSA through public investment. These include several demographic variables, such as percentage nonwhite and percentage of foreign born residents, the geographic size of the MSA, population density, the number of utility patents, and the number of higher education institutions. Finally, an indicator for the MSA's region of the country is included to capture any unobserved regional effects that are not captured by the other variables.[46]

MSA variables are placed into the above categories to help distinguish between variables that can and cannot be improved by public investment. This distinction is important because if the results suggest that one category of amenities are substantially more influential than another category in determining location choice, the implications differ as to whether and how policymakers can attract more highly educated to their city. For instance, if new Ph.D.s are shown to have a relatively high demand for publicly-provided amenities, policymakers may be able to effectively attract more of these workers by investing in the quality of these amenities. Conversely, if publicly-provided amenities are shown to play a relatively small role in the location decisions of new Ph.D.s, policymakers may need to seek out alternative policies, such as promoting better labor opportunities or offering tax incentives for research and development in order to increase the number of highly educated workers in their area.

[46] See Table A.4 in the appendix for a list of MSAs by region.

Table 1

Ph.D. 'Types' by Sector
Graduating Years FY 1997-1999

Ph.D. Type	All	Industry	FTAcademe	Postdocs	Other
(1) Number Trained in a Science & Engineering Field	65,427	16,040	9,019	25,547	14,821
(2) Number from (1) with definite plans	41,670	10,666	6,500	18,951	5,553
(3) Number from (2) with plans in the U.S.	37,395	10,061	5,369	17,336	4,629
(4) Number from (3) with a known U.S. city of employment	25,827	10,018	4,686	11,123	0
(5) Number from (4) in a M.S.A.	22,944	8,880	3,673	10,348	0

Table 2

Inter-State and Inter-Regional Migration Patterns of New S&E Ph.D.s

State/***Region***	Number of New Ph.D.s Trained In State/***Region***	Number of New Ph.D.s Working In State/***Region***	Percentage Gain or Loss	Number of New Ph.D.s Produced that Stay In State/***Region****	Percent of New Ph.D.s Produced that Stay In State/***Region***	Percent of New Ph.D.s Imported from Other States/***Regions***
East North Central	***7712***	***5057***	***-34.4%***	***3065***	***39.7%***	***39.4%***
Illinois	2181	1576	-27.7%	717	32.9%	54.5%
Indiana	1113	580	-47.9%	213	19.1%	63.3%
Michigan	1544	1079	-30.1%	519	33.6%	51.9%
Ohio	1807	1243	-31.2%	633	35.0%	49.1%
Wisconsin	1067	579	-45.7%	287	26.9%	50.4%
East South Central	***1736***	***1288***	***-25.8%***	***656***	***37.8%***	***49.1%***
Alabama	562	349	-37.9%	196	34.9%	43.8%
Kentucky	318	246	-22.6%	96	30.2%	61.0%
Mississippi	279	199	-28.7%	68	24.4%	65.8%
Tennessee	577	494	-14.4%	209	36.2%	57.7%
Mid Atlantic	***6610***	***5737***	***-13.2%***	***3033***	***45.9%***	***47.1%***
New Jersey	906	1322	45.9%	301	33.2%	77.2%
New York	3524	2739	-22.3%	1390	39.4%	49.3%
Pennsylvania	2180	1676	-23.1%	701	32.2%	58.2%
Mountain	***2447***	***2227***	***-9.0%***	***993***	***40.6%***	***55.4%***
Arizona	681	468	-31.3%	207	30.4%	55.8%
Colorado	895	768	-14.2%	330	36.9%	57.0%
Idaho	78	106	35.9%	32	41.0%	69.8%
Montana	101	80	-20.8%	18	17.8%	77.5%
Nevada	10	70	600.0%	**	**	**
New Mexico	255	447	75.3%	104	40.8%	76.7%
Utah	325	233	-28.3%	104	32.0%	55.4%
Wyoming	102	55	-46.1%	25	24.5%	54.5%
New England	***3448***	***3643***	***5.7%***	***1504***	***43.6%***	***58.7%***
Connecticut	619	647	4.5%	175	28.3%	73.0%
Maine	65	90	38.5%	27	41.5%	70.0%
Massachusetts	2271	2502	10.2%	902	39.7%	63.9%
New Hampshire	158	146	-7.6%	37	23.4%	74.7%
Rhode Island	265	175	-34.0%	56	21.1%	68.0%
Vermont	70	83	18.6%	21	30.0%	74.7%
Other	***46***	***72***	***56.5%***	***29***	***63.0%***	***59.7%***
Puerto Rico	46	72	56.5%	29	63.0%	59.7%

Pacific	***6862***	***7637***	***11.3%***	***3988***	***58.1%***	***47.8%***
Alaska	37	41	10.8%	17	45.9%	58.5%
California	5435	6195	14.0%	3112	57.3%	49.8%
Hawaii	109	94	-13.8%	41	37.6%	56.4%
Oregon	467	485	3.9%	142	30.4%	70.7%
Washington	814	822	1.0%	291	35.7%	64.6%
South Atlantic	***6508***	***6092***	***-6.4%***	***3247***	***49.9%***	***46.7%***
Delaware	186	175	-5.9%	39	21.0%	77.7%
District of Columbia	319	420	31.7%	53	16.6%	87.4%
Florida	1130	809	-28.4%	411	36.4%	49.2%
Georgia	1017	731	-28.1%	320	31.5%	56.2%
Maryland	1104	1649	49.4%	429	38.9%	74.0%
North Carolina	1286	1060	-17.6%	471	36.6%	55.6%
South Carolina	381	289	-24.1%	124	32.5%	57.1%
Virginia	950	830	-12.6%	325	34.2%	60.8%
West Virginia	135	129	-4.4%	39	28.9%	69.8%
West North Central	***3042***	***2190***	***-28.0%***	***1173***	***38.6%***	***46.4%***
Iowa	644	331	-48.6%	164	25.5%	50.5%
Kansas	388	233	-39.9%	112	28.9%	51.9%
Minnesota	894	781	-12.6%	330	36.9%	57.7%
Missouri	708	566	-20.1%	241	34.0%	57.4%
Nebraska	267	169	-36.7%	80	30.0%	52.7%
North Dakota	105	66	-37.1%	26	24.8%	60.6%
South Dakota	36	44	22.2%	7	19.4%	84.1%
West South Central	***3259***	***2934***	***-10.0%***	***1518***	***46.6%***	***48.3%***
Arkansas	123	134	8.9%	43	35.0%	67.9%
Louisiana	516	316	-38.8%	164	31.8%	48.1%
Oklahoma	299	219	-26.8%	100	33.4%	54.3%
Texas	2321	2265	-2.4%	1066	45.9%	52.9%
SUM/MEANS U.S.	41670	36877	-11.5%	n/a	n/a	n/a

* The number of new Ph.D.s staying in region includes Ph.D.s who travels between states within a region.

Table 3

Top 25 MSAs in Terms of Production and Employment

PRODUCTION				EMPLOYMENT			
MSA	Number Produced	Number Produced who are Employed in MSA	Percent Who Stay in MSA	MSA	Number Employed	Number Employed who were Trained in MSA	Percent Who Were Trained in MSA
Boston, MA-NH	1808	446	24.7%	Boston, MA-NH	1390	446	32.1%
Los Angeles-Long Beach, CA	1374	371	27.0%	San Jose, CA	1269	261	20.6%
Chicago, IL	1301	338	26.0%	Los Angeles-Long Beach, CA	883	371	42.0%
New York, NY	1217	267	21.9%	Chicago, IL	790	338	42.8%
Oakland, CA	1012	126	12.5%	New York, NY	780	267	34.2%
Washington, DC-MD-VA	924	182	19.7%	Philadelphia, PA-NJ	567	178	31.4%
Madison, WI	921	141	15.3%	Washington, DC-MD-VA	503	182	36.2%
San Jose, CA	871	261	30.0%	Minneapolis-St. Paul, MN-WI	491	206	42.0%
Minneapolis-St. Paul, MN-WI	845	206	24.4%	Oakland, CA	485	126	26.0%
Champaign-Urbana, IL	812	97	11.9%	San Francisco, CA	466	57	12.2%
Greensboro-Winston-Salem,NC	799	150	18.8%	Houston, TX	448	101	22.5%
Philadelphia, PA-NJ	776	178	22.9%	Greensboro-Winston-Salem,NC	427	150	35.1%
Ann Arbor, MI	773	124	16.0%	Seattle, WA	418	162	38.8%
Austin, TX	724	129	17.8%	Baltimore, MD	389	111	28.5%
Pittsburgh, PA	706	152	21.5%	Dallas, TX	380	99	26.1%
Atlanta, GA	700	155	22.1%	San Diego, CA	356	133	37.4%
Lafayette-West Lafayette, IN	656	61	9.3%	Austin, TX	339	129	38.1%
Seattle, WA	643	162	25.2%	Ann Arbor, MI	337	124	36.8%
Baltimore, MD	617	111	18.0%	Atlanta, GA	332	155	46.7%
Columbus, OH	581	110	18.9%	Pittsburgh, PA	330	152	46.1%
San Diego, CA	579	133	23.0%	Newark, NJ	325	21	6.5%
State College, PA	578	69	11.9%	New Haven-Meriden, CT	292	60	20.5%
Sacramento, CA	517	104	20.1%	St. Louis, MO-IL	287	93	32.4%
Tucson, AZ	475	78	16.4%	Madison, WI	271	141	52.0%
Gainesville, FL	472	71	15.0%	Raleigh-Durham, NC	252	109	43.3%
Sum Top 25	*20681*	*4222*	*20.4%*	*Sum Top 25*	*12807*	*4172*	*32.6%*
Sum Non-Top 25	*17096*	*3002*	*17.6%*	*Sum Non-Top 25*	*10155*	*3052*	*30.1%*

Table 4

MSA Variable Definitions and Descriptive Statistics

Variable	Definition	Mean	Std Dev
Natural Amenities			
JanSun	Mean number of hours of January Sunlight	152	40.2
JanTemp	Mean January Temperature in degrees Fahrenheit	36.7	15.4
JulRH	Mean Relative Humidity in July	57.1	15.2
JulTemp	Mean July Temperatures in degrees Fahrenheit	75.8	5.4
PWater	Percent of an MSA's surface area covered by water.	8.1	13.1
Coast	Dummy Variable indicating whether MSA borders Atlantic or Pacific Ocean	0.22	0.41
Publicly Provided Amenities			
Vcrime	Mean number of reported murders, robberies and assaults per 100,000 residents, 1997-1999	562	312
Parkacre	Acres of protected parkland (in thousands) within 25 miles of MSA border in 1999	4.35	23.2
BadAQ	Number of Days that Air Quality Index was labeled as unhealthy in 1999	8.2	10.8
Supfund	Number of "Superfund" Sites on EPA's National Priority List, 1997-1999	3.1	5.7
ArtEnt	Number of art, entertainment, and recreation enterprises per 100,000 residents in 1998	36	13.9
Comtime	Mean commute time to work in minutes in MSA in 1999	22.7	3.8
PupTeach	Student to Teacher Ratios for K-12 in 1998	17.2	2.8
Studexp	Expenditures per student (in thousands) enrolled in K-12 in 1998	5.99	1.2
Other City Characteristics			
NStudnts	Total number of students enrolled in K-12 in 1998 per 100 residents	17.0	2.8
MSASize	Geographic Size of MSA in square miles (in thousands)	2.31	3.25
PopDens	Number of residents (in hundreds) per square mile in MSA in 2000	4.44	0.93
PerDem	Percent of votes in the MSA congressional elections between 1997 and 1999 that were cast for a democratic candidate or against a republican candidate	46.4	16.6
PerBach	Percent of residents age 25 and above in 2000 with a bachelor's degree or higher	23.8	7.4
Pnonwhite	Percent of residents in MSA in 2000 that are not Caucasian	20.3	12.2
Pforborn	Percent of residents in MSA in 2000 that were not born in the U.S.	7.4	7.4
HighEd	Number of 4 year colleges or universities in MSA in 1997	3.4	5.5
Pats	Number of Utility Patents Granted in MSA in 1998 per 100,000 residents	28.0	32.3
Regions			
NorthAtl	Dummy Variable indicating whether MSA lies in North Atlantic Region of U.S.	0.18	0.39
SouthAtl	Dummy Variable indicating whether MSA lies in South Atlantic Region of U.S.	0.18	0.39
NorthCen	Dummy Variable indicating whether MSA lies in North Central Region of U.S.	0.23	0.42
SouthCen*	Dummy Variable indicating whether MSA lies in South Central Region of U.S.	0.21	0.41
Mount	Dummy Variable indicating whether MSA lies in Mountain Region of U.S.	0.08	0.26
Pacific	Dummy Variable indicating whether MSA lies in Pacific Region of U.S.	0.12	0.33

**SouthCen* is the benchmark dummy in all of the models.

CHAPTER 4

PRIVATE CONSUMPTION

This chapter explains the process used to estimate Ph.D.s' income and housing expenditures, and presents results from the estimation of private consumption in their observed MSAs.[47] Because the SED does not offer data on individual salaries or housing expenditures, these are estimated separately using alternative data sources. The data used to estimate Ph.D. salary comes from the Survey of Doctorate Recipients (SDR), which provides the demographic and career information of approximately 30,000 employed Ph.D.s biennially. The sample drawn from the SDR includes full-time employed S&E Ph.D.s in the U.S. in the 1997 and 1999 datasets.[48] From this sample of full-time employed Ph.D.s, wage equations are estimated that relate characteristics of an employee and their job to their annual salary.

This chapter proceeds as follows. Section A describes the SDR data used to estimate annual salary and the specification of the salary equations for Ph.D.s by sector of employment. Because the SDR only reports the U.S. employment state of industrial Ph.D.s (not city), the estimated salaries of industrial Ph.D.s are adjusted to account for the expected variations in income across MSAs. Section B explains the process used to

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[47] As discussed in Chapter 2, the estimation and inclusion of composite consumption plays a vital role in the analysis. The RUM uses a vector of city characteristics, as well as the expected private consumption, to model Ph.D.s' choice of city. The model implicitly assumes that to keep utility constant, Ph.D.s' require higher private consumption levels in cities with lower amenity quality, and vice versa. The coefficient on composite consumption represents an individual's marginal utility of income, and is needed to estimate willingness to pay for changes to amenity quality.

[48] There are 10,447 observations that are in both the 1997 and 1999 SDR datasets. For these observations, we use the more recent 1999 information in the analysis.

adjust the salaries of industrial Ph.D.s. Section C reports the coefficient estimates from the salary regressions for each sector. Finally, section D explains how Ph.D.s' housing expenditures are estimated and reports the predicted measures of private consumption.

A. The Salary Equations

Each sector of employment is considered a separate market. The relevant variables that influence expected salary, as well as the way in which job and individual characteristics are capitalized into salary differ across sectors. Thus, the explanatory variables used to predict salary differ across sectors. All variables included in the salary equations for each sector of employment are defined in Table 5.

Means and standard deviations of explanatory variables for both datasets are reported in Table 6. The table indicates that there are considerable differences between the two datasets, but most of these differences are anticipated. For instance, new Ph.D.s in the SED are on average 14 years younger than doctorates in the SDR, and the SED is composed of a much larger proportion of postdocs (45% in the SED compared to 8% in the SDR). Ph.D.s in the SDR, most of whom already completed their postdocs, contains a much larger proportion of scientists employed in faculty positions (45% in the SDR to 16% in the SED). Regarding personal characteristics, the SDR is composed of a higher proportion of married Ph.D.s, males, whites, and U.S. citizens, while new Ph.D.s in the SED are more likely to have been trained in computer science, and to have earned their degree from a top- ranked, public institution.[49]

[49] Top fields are based on the 1995 National Research Council (NRC) rankings for all fields except medicine and agriculture. The rankings for the majority of fields are based on the "scholarly quality" scores in the NRC rankings for each relevant program at institutions. For field definitions that were broader than the program definitions in the NRC rankings (such as biology), we calculated the mean for

Salaries of Ph.D.s in a faculty position are predicted using characteristics of the individual and their institution of employment. To control for amenity quality as well as unobserved heterogeneity among MSAs, the salary equation includes indicators for the MSA location. Some MSAs are aggregated because they contain a very small number of observations. An MSA is identified separately only if 35 or more Ph.D.s are observed in the MSA. Of the 198 MSAs that employ at least one Ph.D. in full-time academe, 84 MSAs employ 35 or more Ph.D.s. The remaining 114 small MSAs are aggregated with all other small MSAs in the same region. Similarly, all Ph.D.s not employed in a metropolitan area, or "non-MSAs," are grouped into a single dummy with other non-MSAs in the same region. Thus, each full-time academic Ph.D. is identified in one of 102 location dummies for the OLS salary equation: 84 dummies for large MSAs, 9 regional dummies for small MSAs, and 9 regional dummies for non-MSAs.[50]

The specification of the salary equation for full-time academic Ph.D.s is:

$$w_{ij} = \Sigma_{j=1}^{J} \vartheta_{ij} \{\gamma_0 + \gamma_1 wkxp + \gamma_2^{'} P_W + \gamma_3^{'} X_i + \gamma_4^{'} F_i\} + \varepsilon_{ij} \tag{21}$$

where w_{ij} is the annual salary for individual *i* in location *j*, ϑ_{ij} is equal to one if individual *i* lives in location *j*, *wkxp* measures labor market experience, P_W is a vector of employer characteristics, such as Carnegie Classification and institutional rankings, X_i is a vector of individual characteristics including gender, marital status, and race, and F_i represents a

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each rated program applicable to our broader field for each institution. For the fields of medicine and agriculture, we used the 1998 NSF CASPAR data to rank institutions, due to the absence of data for these fields in the NRC rankings. Institutions in these fields were ranked by total federal R&D expenditures at each institution. In the case of biology and medicine, which have a very large number of Ph.D. programs, 75 institutions were included among the top programs. For smaller fields, such as astronomy, the top category includes the top 25 programs. In most other fields, the top category includes the top 50 programs.

[50] Each of the 102 locations employ more than 35 Ph.D.s.

Ph.D.'s field of training.[51] Note that the work experience variable, *wkxp,* equals one for all Ph.D.s in the SED, and some Ph.D.s in the SDR are also in their first year on the market. Thus, salary is predicted out of sample, but not out of range of the SDR.

Estimating salary for Ph.D.s in industry is more complicated than for the academic sector because we do not know the MSA of employment for industrial Ph.D.s in the SDR; only the U.S. state of employment is known.[52] Therefore, the salaries of industrial Ph.D.s are estimated using individual characteristics, characteristics of the institution of degree, and location dummies for the nine U.S. regions.[53] The salary equation for industrial Ph.D.s takes the form:

$$w_{is} = \Sigma_{s=1}^{S} \vartheta_{is} \{\gamma_0 + \gamma_1 wkxp + \gamma_2^{'} P_s + \gamma_3^{'} X_i + \gamma_4^{'} F_i\} + \varepsilon_{is} \tag{22}$$

where w_{is} is the annual salary for individual *i* in region *s*, ϑ_{is} is equal to one if individual *i* lives in region *s*, *wkxp* is work experience, P_s are characteristics of the Ph.D. granting institution such as Carnegie Classifications, X_i represents demographic characteristics and F_i is field of training. The estimated salaries of industrial Ph.D.s are adjusted to account for the expected variation across MSAs. This is discussed further in Section 2 of this chapter.

Unlike the salaries of industrial and full-time academic Ph.D.s, postdoc salaries are relatively constant across cities, and most of the variations occur across fields and

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[51] Characteristics of the Ph.D. granting institution were initially included in the estimated wage equation for full-time academics. However, we did not include them in the final specification because F-tests indicated that the coefficients are jointly equal to zero at the 90% level of confidence.
[52] The SDR only codes the state of employment, not the city. We are able to determine the city of employment for academic Ph.D.s in the SDR through their institution, but there is no indicator in the SDR that allows us to determine the city location of industrial Ph.D.s.
[53] Initially the industrial wage equation used state of employment rather than region of employment. However, F-tests indicated that the coefficients on states within regions are jointly equal to zero at the 90% confidence level for all regions excluding the Pacific.

institutions. Thus, postdoc salaries are predicted using field of training and characteristics of the employing institution, but do not include controls for the employer location. The salary equation for postdocs equals:

$$w_i = \gamma_0^{'} + \gamma_1 P_W + \gamma_2^{'} F_i + \varepsilon_i \tag{23}$$

where w_i is the annual salary of postdoc *i*, P_W are characteristics of the institution of employment, and F_i is a Ph.D.'s field of training.

B. Adjusting Salary of Industrial Ph.D.s

Recall, the salary equation for industrial Ph.D.s does not include location dummies at the MSA level of detail, only at the regional level. These predicted salaries will be biased if there is variation in salaries across MSAs within a region. For example, a Ph.D. in the Southeast would likely earn more in Atlanta, GA than in Macon, GA. The salary equation for industrial Ph.D.s, by using location dummies for regions, can predict the salaries of Ph.D.s in the Southeast; however, this prediction underestimates the true earnings of Ph.D.s in Atlanta, GA and overestimates the expected earnings of Ph.D.s in Macon, GA. To account for the variation in earnings across MSAs, the predicted salary of Ph.D.s in a region are weighted by a measure of the expected variation in earnings in each MSA relative to the mean earnings in the region.

The fact that we do not know the location distribution of Ph.D.s in the SDR further complicates the prediction of industrial Ph.D.'s salary. When there is a large proportion of Ph.D.s in one MSA, the predicted measure of regional salaries will be biased toward that MSA. For instance, because a larger proportion of industrial Ph.D.s in the Southeast finds employment in a dominant MSA like Atlanta compared to a small

MSA like Macon, the predicted salary for a Ph.D. in the Southeast will likely be a closer estimate to the salaries Ph.D.s in Atlanta than of Ph.D.s in Macon. Further, to weight the predicted salary of Ph.D.s in the Southeast solely by an exogenous wage adjustment in each MSA will overestimate the wages of Ph.D.s in Atlanta (more dominant MSAs where Ph.D.s earn more), and underestimate the wages of Ph.D.s in Macon (less dominant MSAs where Ph.D.s earn less). Thus, in addition to applying an exogenous adjustment for variation in salary, the final salary estimate of industrial Ph.D.s salary also accounts for the expected share of Ph.D.s in each MSA.

To further clarify the issue, consider the following example. Assume the predicted salary of Ph.D.s in the Southeast ($\hat{w}_s$) is equal to \$100,000. Furthermore, Ph.D.s in Atlanta earn 30% more on average than other Ph.D.s in the Southeast, and 80% of Ph.D.s in the Southeast are located in Atlanta.[54] If we were to adjust $\hat{w}_s$ for Ph.D.s in Atlanta solely by the 30% differential measure, their new salary estimate will be \$130,000. However, because 80% of industrial Ph.D.s are observed in Atlanta, the \$100,000 estimate for Ph.D.s in the Southeast is much closer to the true salary of Ph.D.s in Atlanta than all other MSAs. Thus, \$130,000 is an overestimate of the true salaries of Ph.D.s in Atlanta. In this example, the predicted salary of industrial Ph.D.s in Atlanta should be increased to account for the fact that Ph.D.s earn more in Atlanta than elsewhere in the Southeast, but decreased to account for the fact that $\hat{w}_s$ is skewed toward Atlanta. Thus, salaries of industrial Ph.D.s are adjusted to correct for both the variation in wages across MSAs, as well as the location distribution of Ph.D.s in a region.

[54] The actual percent of Ph.D.s in Atlanta is much lower (about 20%); we assume that 80% located in Atlanta just to demonstrate the issue.

To calculate the expected variation in earnings and the share of Ph.D.s in each MSA, the 5% 2000 Census Public Use Micro Sample (PUMS) is used.[55] The variation in earnings in MSA *j* is measured as:

$$C_{js} = 1 + \frac{\overline{w}_j - \overline{w}_s}{\overline{w}_s} \tag{24}$$

where $\overline{w}_j$ is the mean salary of industrial Ph.D.s in MSA *j*, and $\overline{w}_s$ is the mean salary of industrial Ph.D.s in region *s*.

The city location choices of all industrial Ph.D.s from the 5% 2000 Census PUMS are used to measure the share of Ph.D.s in each city.[56] This equals:

$$S_{js} = 1 - \frac{n_j}{N_s} \tag{25}$$

where n_j is the number of Ph.D.s observed in MSA *j*, and N_s is the number of Ph.D.s observed in region *s*. Next, each industrial Ph.D.s' competitive regional salary is estimated as:

$$\hat{w}_{is} = \sum_{j=1}^{n} S_{js}\left[\tilde{w}_s(C_{js})\right] \tag{26}$$

where $\hat{w}_{is}$ is the predicted wage for Ph.D. *i* in industry, C_{js} measures the expected variation in salary in MSA *j* relative to the mean wages in region *s*, and S_{js} measures the population distribution across MSAs in region *s*. The variable $\tilde{w}_s$ represents the competitive regional salary of Ph.D.s, or the expected salary in a region if there were no

[55] The 5% Census PUMS offers data on the mean earnings of a sample of industrial Ph.D.s in all U.S. MSAs in 2000 (Census of Population and Housing, U.S. Census Bureau, Department of Commerce).
[56] Note, here we are assuming that the location choices of industrial Ph.D.s in the Census PUMS data accurately represent the location choice of industrial Ph.D.s in the SDR.

variation in salary across MSAs. Substituting equations (24) and (25) into (26) yields the competitive salary of Ph.D. *i* in region *s*:

$$\tilde{w}_{is} = \frac{\hat{w}_{is}}{\sum_{j=1}^{n} (S_{js} * C_{js})} = \frac{\hat{w}_{is}}{\sum_{j=1}^{n} \left[\left(1 - \frac{n_j}{N_s} \right) * \left(1 + \frac{\overline{w}_j - \overline{w}_s}{\overline{w}_s} \right) \right]} \tag{27}$$

Intuitively, equation (27) states that a Ph.D.'s competitive salary in a region is equal to her predicted salary over the weighted sum of the expected variations in salary for all MSAs in that region. Finally, the expected salary for all industrial Ph.D.s equals the competitive salary in region *s* $\tilde{w}_{is}$, weighted by C_{js}, the variation in salary in MSA *j* relative to the mean salary in region *s*:

$$\hat{w}_{ij} = \tilde{w}_{is} * C_{js} \tag{28}$$

C. Salary Estimation Results

Table 7 presents the results from the OLS salary equations for all three employment sectors. In both academe and industry, the coefficients for the linear and square term of work experience are positive and significant, suggesting that salary increases at an increasing rate with job experience. Controlling for work experience, age negatively affects salary, although the age penalty decreases as one gets older. Personal characteristics such as citizenship, marital status, and race, do not have a statistically significant relationship with salary among either academic or industrial scientists. In addition, males are found to earn more than females in both sectors, and Ph.D.s who are married with at least one child have higher salaries than single people in academe, however this relationship is not significant in industry.

The estimated coefficients on field of training are consistent across sectors. For instance, engineers and computer scientists have higher salaries than the benchmark, biologists, in all sectors. Chemical engineers earn the most of full-time academics, while computer scientists earn the most of industrial scientists and postdocs, everything else constant. By way of contrast, none of the field coefficients are negative and significant relative to the benchmark (biology) in academe or industry. The coefficient on chemistry is negative and significant in the postdoc sector.

Table 8 reports the mean predicted salaries of new Ph.D.s in each sector by field of training. As expected, industrial Ph.D.s earn more on average than their counterparts in academe. The average salary of an industrial Ph.D. in the SDR is slightly over $88,000, and the mean predicted salary is $67,504 for a Ph.D. in industry in their first year. Faculty in the SDR earn approximately $66,600 on average, and the mean predicted earnings for new faculty is $44,854.[57] Postdocs have the lowest earnings of three sectors. The average an annual salary of postdocs in the SDR is approximately $30,000, and $27,724 for postdocs in their first year.

The estimates in Table 8 show that there is a large disparity in average salaries across fields of training. The predicted mean salaries of computer scientists are the highest of all fields in all three sectors. The difference between the mean salary of computer scientists and the mean salary of all other fields is more than $20,000 for postdocs and Ph.D.s in the industrial sector. The strong predicted earnings of computer scientists likely reflects the time period of the analysis, when the technology bubble was at its peak and there was a particularly strong demand for highly trained computer scientists. The estimated earnings are consistently high for engineers, particularly in the

[57] Note that the predicted salary of faculty represents their 12 month salary.

two academic sectors. New chemists have the lowest average salary in the postdoc sector and the second lowest salary to astronomers in full-time academe. In industry, agricultural scientists have the lowest predicted salary, more than $30,000 less than the expected salary of computer scientists.

To gauge the accuracy of our salary predictions, Table 9 compares the predicted salaries in eight S&E fields across sectors to those from a 1998 survey on Ph.D. starting salaries performed by the Commission on Professionals in Science and Technology (CPST).[58] Our median salary predictions in these eight fields are relatively consistent with the results from the CPST study. For instance, of the twenty-four comparable medians between the CPST study and our estimates, ten are within 5% of the other, twenty-one are within 10%, and all of our predicted salaries are within 35% of the results from the CPST survey.

In addition, the relative differences between salaries across fields are highly consistent between the CPST survey and our predictions. For example, in both the CPST survey and our predictions, computer scientists have the highest median salary of all fields in industry and in the postdoc sector, chemical engineers have the highest salary in academe, biochemists and molecular biologists have the lowest salary in industry, and chemists have the lowest of all postdocs. Based on this comparison, we believe that the predicted salaries of Ph.D.s are within a reasonable range of the actual starting salaries of Ph.D.s in the sample.

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[58] Source: "Employment of Recent Doctoral Graduates in Science and Engineering." Commission on Professionals in Science and Technology. August, 1998.

D. Housing Payments

To impute annual housing payments we use the 5% 2000 Census PUMS, which offers mean monthly mortgage payments and monthly rents in all U.S. MSAs for several income brackets.[59] Ph.D.s expected housing costs are based on the mean housing expenditures of people with similar incomes.[60] Specifically, each Ph.D. is categorized into an income bracket based on their predicted salary, and their housing expenditures are defined as the mean rents or mortgage payments of all people in an MSA that are in their income bracket.

Because predicted incomes of postdocs are generally much lower than Ph.D.s in the other sectors, and they are likely to move to a new city once they complete their postdoc, we assume all postdocs rent an apartment rather than purchase a home. Thus, a postdoc's housing cost estimate is given by the mean annual rents (not mortgage payments) in an MSA for the following four income brackets: \$10,000-\$19,999, \$20,000-\$29,999, \$30,000-\$44,999, and \$45,000-\$64,999.

Conversely, faculty and industrial positions are more permanent than postdoctoral appointments, and Ph.D.s in these sectors are more likely to have purchased a home (or eventually will purchase a home) in their MSA.[61] Thus, the housing expenditure estimate for industrial Ph.D.s and faculty is given by the mean annual mortgage payments in an

[59] The 5% PUMS has 51 separate datasets for the 50 states and Washington D.C. For the 39 MSAs that cross state lines, we calculate a weighted mean of rents in that MSA based on the number of people located in each state.
[60] As opposed to relating housing costs with education level which would require the stringent assumption that all people with a Ph.D. buy similar housing, regardless of income level. We could not use both education and income levels to define housing costs due to Census confidentiality restrictions.
[61] The assumption here is not that all industrial and full-time academic Ph.D.s immediately buy a home in their MSA, but rather, that they base their decision of where to live on the cost of purchasing a home in each MSA, not the cost of renting an apartment.

MSA for the following income brackets: \$20,000-\$34,999, \$35,000-\$49,999, \$50,000-\$64,999, \$65,000-\$74,999, and \$75,000 and above.

The final measure of private consumption also accounts for the expected amount Ph.D.s pay in taxes in their MSA. Thus, Ph.D.s' predicted salary is reduced by the expected amount to be paid in both federal and state income taxes, and for homeowners, the expected amount paid in property taxes in their MSA.[62] Table 10 reports the final estimates of after tax income, housing expenditures and private consumption for all Ph.D.s by sector.[63] Housing expenditures account for approximately one third of a Ph.D.s net income, and this figure is proportionally consistent across the three sectors. The mean private consumption of all Ph.D.s is approximately \$22,000. Industrial Ph.D.s, who generally pay more in taxes and are more likely to locate in larger MSAs with higher housing costs and property taxes, have an estimated average private consumption of \$31,316. The average composite consumption of faculty and postdocs is \$21,273 and \$14,228, respectively.

[62] Both federal and state income taxes come from the Federation of Tax Administrators (1999). The data for property taxes comes from the 1999 *Places Rated Almanac*, which offers the average amount a household with \$75,000 income will pay in property taxes in all MSAs.
[63] The average composite consumption changes when different alternative cities are selected into Ph.D.s' choice sets. The measures reported in Table 11 are for Ph.D.s observed city choices.

Table 5

Definitions of Variables Included in Wage Equations
by Sector of Employment*

Variable Name	Variable Description	Industry	FT Academe	Postdoc
Salary	Annual Income of Ph.D. in 1997 or 1999	XX	XX	XX
Demographic Characteristics:				
Wkexp	Years of work experience	X	X	
Wkexpsq	Years of work experience squared	X	X	
Age	Age of the individual	X	X	
Agesq	Age of the individual squared	X	X	
Citizen	Dummy variable indicating whether or not an individual is a U.S. citizen	X	X	
Married	Dummy variable indicating whether or not an individual is married	X	X	
Wchild	Dummy variable indicating whether or not an individual is married with at least one child	X	X	
Male	Dummy variable indicating whether or not an individual is male	X	X	
White	Dummy variable indicating whether or not an individual is white	X	X	
Asian	Dummy variable indicating whether or not an individual is Asian or pacific islander	X	X	
Fields of Training:				
Aere	Dummy variable indicating whether or not an individual's field of training was aerospace engineering	X	X	X
Chee	Dummy variable indicating whether or not an individual's field of training was chemical engineering	X	X	X
Cive	Dummy variable indicating whether or not an individual's field of training was civil engineering	X	X	X
Elee	Dummy variable indicating whether or not an individual's field of training was electrical engineering	X	X	X
Mece	Dummy variable indicating whether or not an individual's field of training was mechanical engineering	X	X	X
Oeng	Dummy variable indicating whether or not an individual's field of training was other engineering	X	X	X
Astr	Dummy variable indicating whether or not an individual's field of training was astronomy	X	X	X
Agri	Dummy variable indicating whether or not an individual's field of training was agriculture	X	X	X
Biol**	Dummy variable indicating whether or not an individual's field of training was biology	X	X	X
Chem	Dummy variable indicating whether or not an individual's field of training was chemistry	X	X	X
Phys	Dummy variable indicating whether or not an individual's field of training was physics	X	X	X
Math	Dummy variable indicating whether or not an individual's field of training was mathematics	X	X	X
Comp	Dummy variable indicating whether or not an individual's field of training was computer science	X	X	X
Earth	Dummy variable indicating whether or not an individual's field of training was earth science	X	X	X

Medi	Dummy variable indicating whether or not an individual's field of training was in a medical related field	X	X	X
Characteristics of Ph.D. Granting Institution:				
PrivPh.D.	Dummy variable indicating whether or not an individual received their Ph.D. from a private institution	X	X	
Top110Ph.D.	Dummy variable indicating whether or not an individual received their Ph.D. from a top 110 institution	X	X	
TopfldPh.D.	Dummy variable indicating whether or not an individual received their Ph.D. from a top ranked institution their field	X	X	
Ru1Ph.D. [a]	Zero-one dummy if Carnegie classification of school awarding degree is Research University I.	X	X	
Ru2Ph.D.	Zero-one dummy if Carnegie classification of school awarding degree is Research University II	X	X	
Doc1Ph.D.	Zero-one dummy if Carnegie classification of school awarding degree is Doctoral Granting I.	X	X	
Doc2Ph.D.	Zero-one dummy if Carnegie classification of school awarding degree is Doctoral Granting II.	X	X	
MedicoPh.D. **	Zero-one dummy if Carnegie classification of school awarding degree is Medical school or anything besides Ru1, Ru2, Doc1 and Doc2 dummies.	X	X	
Characteristics of Employing Institution:				
Privemp	Dummy variable indicating whether or not an individual works for a private institution		X	X
Top110emp	Dummy variable indicating whether or not an individual works for a top 110 institution		X	X
Topfldemp	Dummy variable indicating whether or not an individual works for a top ranked institution their field		X	X
Ru1emp	Zero-one dummy if Carnegie classification of school of employment is Research University I.		X	X
Ru2emp	Zero-one dummy if Carnegie classification of school of employment is Research University II		X	X
Doc1emp	Zero-one dummy if Carnegie classification of school of employment is Doctoral Granting I.		X	X
Doc2emp	Zero-one dummy if Carnegie classification of school of employment is Doctoral Granting II.		X	X
Compemp	Zero-one dummy if Carnegie classification of school of employment is a Comprehensive institution.		X	X
Libartemp	Zero-one dummy if Carnegie classification of school of employment is a Liberal Arts Institution.		X	X
Mediemp**	Zero-one dummy if Carnegie classification of school of employment is a Medical school.		X	X
Otheremp	Zero-one dummy if Carnegie classification of school of employment is Ru1, Ru2, Doc1 and Doc2, Comp, Libart, or Medi.		X	X

×× Indicates the variable is a dependent variable included in the equation
× Indicates the variable is an explanatory variable included in the equation
**Indicates the benchmark or control group.
a) We use the Carnegie classifications of institutions as coded in the Survey of Earned Doctorates.

Table 6

Means by Sector from the SED and SDR 1997 -1999

	Survey of Earned Doctorates (SED)					Survey of Doctorate Recipients (SDR)*			
Variable	Al Sectors (n=22903)	Industry (n=8873)	Full-Time Academe (n=3681)	Postdoc (n=10349)		ALL Sectors (n=413892)	Industry (n=206411)	Full-Time Academe (n=183966)	Postdoc (n=23515)
SALARY	n/a	n/a	n/a	n/a		77129	90187	68460	30331
Demographic Characteristics:									
wkexp	1	1	1	1		14.8	14.1	17.0	2.7
wkexpsq	1	1	1	1		327.0	296.4	401.7	10.7
Age	32.7	32.31	36.02	31.77		46.1	45.3	48.5	34.7
Agesq	1096	1068	1356	1026		2229	2145	2451	1229
Citizen	0.62	0.55	0.82	0.61		0.85	0.82	0.92	0.65
Married	0.58	0.61	0.62	0.54		0.81	0.83	0.81	0.63
Wchild	0.40	0.44	0.44	0.35		0.50	0.54	0.47	0.35
male	0.70	0.81	0.58	0.66		0.82	0.86	0.78	0.64
white	0.62	0.55	0.80	0.63		0.78	0.72	0.86	0.67
asian	0.31	0.39	0.12	0.30		0.20	0.26	0.11	0.30
Fields of Training:									
aere	0.01	0.016	0.004	0.005		0.01	0.01	0.01	0.01
chee	0.04	0.08	0.01	0.02		0.04	0.06	0.01	0.01
cive	0.02	0.03	0.03	0.01		0.02	0.03	0.03	0.01
elee	0.09	0.20	0.05	0.02		0.07	0.10	0.04	0.01
mece	0.04	0.07	0.03	0.02		0.05	0.07	0.03	0.01
oeng	0.08	0.13	0.06	0.04		0.06	0.08	0.04	0.03
astr	0.01	0.00	0.01	0.01		0.01	0.00	0.01	0.01
agri	0.03	0.02	0.04	0.03		0.04	0.04	0.05	0.03
biol	0.26	0.06	0.15	0.47		0.25	0.17	0.31	0.58
chem	0.12	0.12	0.06	0.14		0.13	0.18	0.08	0.09
phys	0.06	0.07	0.03	0.07		0.08	0.09	0.07	0.07
math	0.06	0.05	0.15	0.04		0.07	0.04	0.10	0.03
comp	0.05	0.08	0.09	0.01		0.02	0.03	0.02	0.00
earth	0.03	0.02	0.03	0.03		0.03	0.02	0.04	0.02
medi	0.09	0.04	0.26	0.08		0.12	0.08	0.16	0.09
Characteristics of Ph.D. Granting Institution:									
privPh.D.	0.31	0.32	0.26	0.32		0.68	0.67	0.68	0.66
top110Ph.D.	0.84	0.84	0.79	0.86		0.60	0.60	0.59	0.80
topPh.D.fld	0.68	0.69	0.61	0.70		0.48	0.48	0.47	0.67
ru1Ph.D.	0.77	0.78	0.73	0.78		0.77	0.76	0.78	0.77
ru2Ph.D.	0.09	0.09	0.11	0.08		0.11	0.11	0.10	0.08
doc1Ph.D.	0.04	0.05	0.06	0.03		0.05	0.06	0.05	0.03
doc2Ph.D.	0.04	0.05	0.05	0.03		0.04	0.04	0.03	0.03
medicoPh.D.	0.05	0.02	0.05	0.07		0.03	0.03	0.03	0.08
Characteristics of Employing Institution:									
privemp	0.19	n/a	0.26	0.32		0.17	n/a	0.32	0.44
top110emp	0.49	n/a	0.49	0.90		0.29	n/a	0.55	0.88
topempfld	0.40	n/a	0.36	0.77		0.22	n/a	0.40	0.77

ru1emp	0.43	n/a	0.41	0.80		0.24	n/a	0.45	0.76
ru2emp	0.03	n/a	0.06	0.05		0.04	n/a	0.09	0.05
doc1emp	0.01	n/a	0.04	0.01		0.02	n/a	0.05	0.01
doc2emp	0.03	n/a	0.07	0.03		0.03	n/a	0.07	0.03
compemp	0.04	n/a	0.21	0.01		0.08	n/a	0.18	0.01
libartemp	0.02	n/a	0.10	0.00		0.03	n/a	0.07	0.01
mediemp	0.03	n/a	0.03	0.06		0.03	n/a	0.06	0.09
otheremp	0.02	n/a	0.06	0.03		0.02	n/a	0.04	0.04

*Reported means are weighted in the Survey of Doctorate Recipients to represent the population of doctorate holders in the U.S. No such weights exist for the Survey of Earned Doctorates.

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Table 7
OLS Results for Salary Equation: SDR by Sector

	ACADEME		INDUSTRY		POSTDOC	
	N=10633 R-sq=0.335		N=11469 R-sq=0.209		N=1768 R-sq=0.163	
Variable Name	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**
Intercept	54986***	4.33	59160***	3.44	30391***	36.69
Demographic Characteristics:						
Wkexp	3106***	3.75	7397***	6.2	n/a	n/a
Wkexpsq	25***	3.69	60***	5	n/a	n/a
Age	-1411**	-2.43	-1157	-1.34	n/a	n/a
Agesq	24***	3.35	23**	2.05	n/a	n/a
Citizen	1974	1.09	1220	0.67	n/a	n/a
Married	459	0.35	883	0.53	n/a	n/a
Wchild	1451	1.20	2508*	1.69	n/a	n/a
Male	2468**	2.21	3256**	2.08	n/a	n/a
White	-192	-0.11	-3560	-1.19	n/a	n/a
Asian	-3331	-1.46	-4672	-1.47	n/a	n/a
Fields of Training:						
Aere	7177	1.24	3924	0.78	12484***	4.67
Chee	19352***	4.55	4915*	1.77	4845***	2.91
Cive	12889***	4.34	3249	0.84	12192***	6.21
Elee	12613***	5.38	16553***	7.42	10078***	6.63
Mece	8867***	3.12	5726**	2.13	8056***	4.51
Oeng	14624***	6.32	7828***	3.10	3732**	3.18
Astr	-1100	-0.21	3153	0.33	7238***	4.04
Agri	237	0.09	-2744	-0.70	934	0.82
Chem	1296	0.62	2246	1.00	-1699**	-2.42
Phys	3362	1.45	3014	1.15	6040***	7.64
Math	1165	0.59	4727	1.35	9951***	9.65
Comp	16940***	5.73	22482***	6.47	15043***	5.97
Earth	62	0.02	-1376	-0.32	5768***	5.18
Medi	7574***	5.29	8030***	3.02	351	0.56
Characteristics of Ph.D. Granting Institution:						
PrivPh.D.	-1231	-1.10	-3963***	-3.00	n/a	n/a
Top110Ph.D.	848	0.53	146*	0.07	n/a	n/a
TopfldPh.D.	-670	-0.45	2887	1.54	n/a	n/a
Ru1Ph.D.	-1985	-0.85	9685***	2.74	n/a	n/a
RU2Ph.D.	-1106	-0.41	6969*	1.84	n/a	n/a
Doc1Ph.D.	-5361*	-1.76	6698	1.60	n/a	n/a
Doc2Ph.D.	-2052	-0.61	10273**	2.37	n/a	n/a
Characteristics of Employing Institution:						
Privemp	-2490*	-1.85	n/a	n/a	1071***	2.89
Top110emp	-3913*	-1.81	n/a	n/a	-1981**	-2.21
Topfldemp	2810*	1.67	n/a	n/a	602	0.98
Ru1emp	3549	1.36	n/a	n/a	-1128*	-1.65
Ru2emp	-3536	-1.24	n/a	n/a	-2596**	-2.42
Doc1emp	-194	-0.06	n/a	n/a	-4852***	-2.64
Doc2emp	-5893**	-2.12	n/a	n/a	-2634**	-2.24
Compemp	-5902**	-2.44	n/a	n/a	-1229	-0.73
Libartemp	-7316**	-2.56	n/a	n/a	186	0.08
Otheremp	1023	0.33	n/a	n/a	-1011.716	-0.88

* (**) [***] Statistically significantly different from zero at the 10% (5%) [1%] level of significance.

Table 8

Means and (Std. Dev.) of Predicted Salaries by Field and Sector

	Industry	FT Academe	Postdocs
All S&E	$67,504 (14460)	$44,853 (9443)	$27,724 (5210)
Aerospace Engineering	$64,751 (10199)	$47,722 (4205)	$34,926 (1270)
Chemical Engineering	$62,270 (12260)	$55,367 (6250)	$31,233 (1783)
Civil Engineering	$62,411 (9917)	$51,934 (6291)	$39,136 (1576)
Electrical Engineering	$78,501 (11076)	$51,582 (6212)	$36,948 (1566)
Mechanical Engineering	$63,727 (10379)	$46,190 (6552)	$36,990 (1505)
Other Engineering	$66,054 (11275)	$53,629 (7086)	$30,529 (1658)
Agriculture	$54,388 (12751)	$39,117 (4926)	$25,392 (1677)
Astronomy	$63,219 (8632)	$36,680 (8621)	$35,223 (1618)
Biology	$58,200 (11399)	$39,321 (7037)	$25,190 (1761)
Chemistry	$60,070 (12991)	$37,402 (6289)	$23,714 (1699)
Computer Science	$86,704 (11717)	$54,597 (7618)	$47,052 (1742)
Earth Science	$59,854 (8990)	$37,967 (7005)	$31,893 (1585)
Math	$63,748 (11046)	$37,640 (6595)	$38,813 (1448)
Medicine	$63,855 (13764)	$48,161 (7533)	$26,235 (2030)
Physics	$62,735 (9769)	$41,195 (7763)	$33,842 (1582)

Table 9

1998 CPST Median Salary Results* and OLS Median Salary Estimates

	CPST Median Salaries				Our Predicted Median Salaries		
Field of training	Industry	FT Academe	Postdoc		Industry	FT Academe	Postdoc
Biochemistry & Molecular Biology	$53,000	$26,500	$25,250		$56,999	$38,879	$25,196
Chemistry	$58,000	$34,000	$25,000		$60,149	$37,005	$23,717
Chemical Engineering	$61,200	$64,000	$33,000		$63,184	$55,031	$31,222
Computer Science	$72,500	$56,500	$44,000		$84,729	$54,313	$47,058
Earth sciences	$58,600	$40,000	$34,000		$59,315	$37,890	$31,791
Engineering	$63,600	$55,000	$35,250		$69,420	$51,467	$35,252
Mathematics	$60,000	$49,700	$37,500		$63,063	$37,316	$38,822
Physics	$62,000	$45,000	$36,000		$61,259	$40,759	$33,960

* Source: "Employment of Recent Doctoral Graduates in Science and Engineering." Commission on Professionals in Science and Technology. August, 1998.

Table 10

Means and (Std. Dev.) of Net Income, Housing Payments and Private Consumption of New Ph.D.s by Sector

Sector	N	Net Income	Housing Payments	Private Consumption
All	22679	$33,309 (12964)	$11,328 (4564)	$21,981 (9635)
Industry	8801	$46,517 (9317)	$15,201 (4341)	$31,316 (7129)
Full-Time Academe	3611	$32,394 (6163)	$11,122 (2625)	$21,273 (5866)
Postdoc	10267	$22,309 (3554)	$8,081 (2004)	$14,228 (3793)

CHAPTER 5

RESULTS FROM RANDOM UTILITY MODEL ESTIMATION

This chapter presents results from several random utility models using the choice probability equations described in Chapter 2. The primary objective of this chapter is to explore the effects of modeling technique on the coefficient estimates, and to establish a set of preferred results to be used later in Chapter 6 to compute Ph.D.s' willingness to pay for changes in the level of amenities in MSAs. Thus, this chapter focuses on the stability of the coefficient estimates and significance levels across models, and discusses whether the estimates from each model accord with prior expectations. [64]

The chapter has several components. Sections A and B report estimates from the conditional logit models that are used to determine the appropriate specifications for the more advanced random utility models. Specifically, section A presents results from models using the full sample of all new Ph.D.s in S&E. These are compared to the models presented in section B, which restrict the analysis to Ph.D.s without contractual obligations to a previous employer. The models in these two sections assume preferences for city attributes are homogeneous across the population of Ph.D.s. In section C, this assumption is relaxed and conditional logit models are estimated that account for observed heterogeneity in preferences by introducing interaction terms between individual characteristics and city attributes.

[64] All of the models presented in this chapter are estimated using NLOGIT 3.0, a separate software component of Limdep 7.0.

Section D tests for possible IIA violation and bias to the estimates in the conditional logit models. Although the test results suggest the conditional logit models exhibit the IIA property, less restrictive random utility models are estimated to further explore the impact of amenities on location choice. Section E presents results from the nested logit model, and Section F presents results from the mixed (random coefficients) logit model. Finally, Section G concludes with a summary of the key results of this chapter.

A. Simple Conditional Logit Models Results

This section presents and compares results from several simple conditional logit models that estimate Ph.D. MSA choice. We explore the robustness and consistency of the models to various factors that may affect the coefficient estimates. These factors include: 1) choice set size (the number of alternative cities included in each Ph.D.'s choice set) 2) the specific set of alternative cities selected to each Ph.D.'s choice set, and 3) the type of Ph.D.s included in the analysis. To examine the potential influence of the number of alternative cities included in the estimation, separate models are estimated with choice sets of size six (five alternatives plus the observed city), eleven (ten alternatives plus the observed city), and twenty six (twenty five alternatives plus the observed city). [65] To examine the sensitivity of the parameters to the specific set of cities selected, each model is estimated using three separate draws of alternative cities for each choice set size. Thus, the tables to follow present results for nine separate conditional logit models (3 choice set draws * 3 different sized choice sets).

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[65] Recall, the choice set for each individual includes the selected alternative cities and each individual's chosen city. Duplicate cities are deleted for each individual, such that the choice set sizes are not equal across individuals. See Chapter 2 for a detailed description of the choice set selection process.

The choice sets used in each model are selected in the same manner (as described in Chapter 2, Section F), and there is no basis *a priori* to prefer one set of results to another. Theoretically, the models estimated with smaller choice sets may have biased coefficients if the choice sets systematically exclude relevant alternatives (cities that were likely to be considered by Ph.D.s). Conversely, the models estimated with larger choice sets may have biased coefficients if the choice sets systematically include cities that were not considered as potential cities of employment by Ph.D.s.

Table 11 presents the coefficients estimates from the nine conditional logit models estimated with the full sample of Ph.D.s. Models 1-3 (Columns 2-4 in Table 11) report the coefficient estimates for three models estimated with choice sets of 6 cities; models 4-6 (Columns 5-7) report the coefficients for three models estimated with choice sets of 11 cities; and models 7-9 (Columns 8-10) report the coefficients for three models estimated with choice sets of 26 cities. The results include an indicator of the significance level of each coefficient, but t-statistics and standard errors are not reported due to lack of space. The estimation is conducted on the full sample of 22,666 Ph.D.s that had non-missing values for private consumption and MSA data. The explanatory variables are the same in each model. Specifically, the models estimate coefficients (preferences) for private consumption, distance between the location of degree and job location, and the twenty-eight MSA characteristics reported in Table 4.

In all of the models, the sign of a coefficient indicates the effect of a unit increase in the value of the attribute on a Ph.D.s' indirect utility function (equation 5). For instance, a positive coefficient on January temperatures would indicate that Ph.D.s prefer warmer winters, or that MSAs with warmer winters have a higher probability of being chosen by Ph.D.s, other things equal. The coefficients imply ordinal preference for an attribute, however, the magnitudes of the reported coefficients are only meaningful in determining willingness to pay and implicit prices of city attributes, which are reported and discussed in the Chapter 6. Thus, the discussion centers on the signs and significance levels, rather than magnitudes of the coefficients.

Table 11 indicates that the signs of the coefficients are not sensitive to the set of alternative cities included in the choice set. Of the 30 variables in the model, 21 coefficients have the same sign in all nine regressions, and 27 have the same sign in at least eight of the nine models. Although the coefficient signs are stable across choice sets, there is noticeable variation in the significance levels of the coefficients across models. In general, the standard errors decrease as the choice set size increases. At least 19 of the 30 coefficients are significant at the 10% level or better in all of the models that are estimated with 25 alternative cities in the choice set. No more than 16 coefficients are significant when the models are estimated with 10 alternative cities, and there are never more than 14 significant coefficients when the models are estimated with only 5 alternative cities.[66]

As indicated in Table 11, the coefficient on private consumption (*compcons*), which is particularly important for estimating implicit prices and willingness to pay, is reliably positive and significant at the 5% level or better in all nine models. This result indicates that new Ph.D.s prefer cities where they can expect to receive a higher net income, other things equal. The variable *distance* is included to control for the direct and psychological costs associated with migrating to a new city. The psychological costs

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[66]Feather (1994) and Parsons and Kealy (1992) also find stable coefficients across models with different sized choice sets, and that the standard errors decrease as choice set size increases.

associated with moving are arguably lower for a Ph.D. at the time of degree than it would be during other times in their career due to the fact that a number of a new Ph.D.'s peers are also likely to be moving at the same time. The effect of distance variable is also related to a number of observable characteristics, such as marital status, age, etc., as well as a number of unobservable characteristics, such as how distance moved will influence an individual's ability to collaborate on research projects with their adviser.[67] As expected, the coefficient on distance is negative and significant at the 1% level in all nine models, suggesting that Ph.D.s are more likely to locate in cities that are geographically closer to where they receive their degree.[68]

With the exception of percent of lakes and streams (*PWater*) and hours of January sunlight (*JanSun*), the signs of the coefficients on natural amenities are consistent with prior expectations. The coefficient on *JanSun* is consistently negative, and significant at the 10% level or better in five of the nine models. Cragg and Kahn (1997) also find mixed results for their 'sunshine' variable. Specifically, of the twelve model results presented by the authors, the coefficient on the comparable variable is either not statistically significant or negative in nine of the models. The coefficient estimates for *JanSun* likely does not accurately represent the true preference for sunlight in winter, but rather, is likely capturing the influence of an unobserved variable. One possibility is the "Pacific Northwest" (NW) effect. That is, MSAs in the Pacific NW region (Washington and Oregon) have a relatively low amount of January sunlight, but are large employers of

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[67] The hybrid models presented in Section 3 of this chapter introduce controls for heterogeneity on the distance variable.

[68] Although this makes intuitive sense, an additional model was estimated to assess the robustness of the distance effect. Specifically, the coefficient on distance remains negative and significant when the sample excludes Ph.D.s who stay in the same state after degree. This suggests that the further an MSA is from a Ph.D.'s current location, the less likely it will be chosen by Ph.D.s who migrate to a new state.

S&E Ph.D.s. Thus, the negative coefficient on *JanSun* may reflect a preference for the shared unobserved characteristics within the Pacific NW. To test for this, we also estimated additional models with a separate indicator for the Pacific NW region.[69] The coefficients on *JanSun* are not statistically significant in all of these models, and the coefficient on Pacific NW is positive and significant. These results suggest that the negative coefficients on *JanSun* are at least somewhat driven by the unobserved characteristics within the Pacific Northwest.

The coefficients on the other climate variables, namely January temperatures (*JanTemp*), July temperature (*JulyTemp*), and July relative humidity (*JulyRH*) all have the anticipated signs. Specifically, *JanTemp* is positive and significant, while the coefficients on *JulyTemp*, *JulyRH* are both negative and significant at the 10% level or better in the majority of the models.[70] These results suggest that new Ph.D.s prefer more moderate-arid climates, or cities with warmer winters and cooler, dryer summers. The last natural amenity variable included in the models is an indicator for whether the MSA lies on the coastline (*Coast*). The coefficients on *Coast* are positive and significant in the majority of the models, suggesting that new Ph.D.s are more likely to locate in cities near the ocean, other things equal.

The coefficients on the publicly-provided amenity variables are less consistent with expectations. For example, the coefficient on *SupFunds* is positive and significant in the majority of equations, suggesting that new Ph.D.s prefer cities with more superfund sites to less. This perplexing result is likely an outcome of the aggregation of

[69] Note that because the Pacific region is comprised of California and the Pacific Northwest, including an indicator for the Pacific NW is equivalent to introducing a dummy for California.
[70] The coefficients on *JanTemp, JulyTemp,* and *JulyRH* are consistent with the results reported in Cragg and Kahn (1997)

alternatives. In other words, the presence of a superfund sites may only affect an individual's utility if it is within close proximity to their residence. Even if an MSA has a large number of superfund sites, if individuals can find a home that is not in close proximity to one of them, it might not affect their choice of MSA. Thus, the presence (number) of a superfund site(s) likely impacts the choice of a residential area within an MSA, but not the choice of MSAs. The aggregation bias, however, does not explain why the coefficient on number of superfund sites is statistically significant in seven of the models. The positive and significant coefficients could be related to the larger presence of superfund sites in highly industrialized areas. To test for this possibility, we included total industrial productivity in an MSA as an explanatory variable, but found the coefficients on *SupFunds* remained positive and significant.

The variables indicating acres of parkland (*ParkAcre*) and number of art and entertainment enterprises (*ArtEnt*) are included in the models to capture the effects of recreational opportunities in MSAs. The coefficient on *ParkAcre* is negative and significant in two models, and the coefficient on *ArtEnt* is negative and significant in five models. Although counterintuitive, a strict interpretation would suggest that new Ph.D.s prefer MSAs with fewer recreational opportunities, other things equal.

Not all of the coefficients on publicly-provided amenities are counterintuitive. The results indicate that new Ph.D.s prefer cities with higher air quality and lower commute times, other things constant. Air quality in an MSA, as measured by the number of “unhealthy” AQI days, has a negative and significant coefficient in all nine models, and the coefficient on commute time to work is negative and significant in seven of the nine models. Furthermore, the coefficient on violent crimes (*VCrime*) is negative in all nine models as expected, but not significant. The results also indicate that new Ph.D.s prefer cities where public schools have lower student to teacher ratios, other things constant.

In addition, the coefficient for expenditures per student (*Studexp*) is negative and significant in four of the nine models. We have no priors regarding this coefficient. It could be argued that student expenditures measure school quality (and thus be desirable) or the amount of inefficiency in public schools (and thus be undesirable). There is no consensus among educational economists as to whether or not higher student expenditures result in better student outcomes. For example, Hanushek (1998) finds that expenditures per student are not significantly related with school quality.

The results support the hypotheses of the "talent" literature, namely, that the highly educated prefer cities with larger amounts of diversity. In this model, diversity is measured by the percent foreign born (*Pforborn*) and the percent of minority residents (*Pnonwhite*) in an MSA. The coefficients on *Pforborn* are positive and significant in all nine models, and the coefficients on *Pnonwhite* are positive in eight of the nine models, but not significant. The effect of 'political leanings' of a city, as measured by the percent of the population that voted for a Democratic candidate (*PerDem*), is of special interest because no such measure has been included in previous analyses. The coefficient on *PerDem* is positive in all nine models and significant at the 10% level in four of the nine models, indicating that, other things equal, new Ph.D.s prefer cities in which the population is more likely to vote for a representative from the Democratic Party.

The models suggest that the innovative nature of the community matters, as measured by the number of utility patents granted to residents in the MSA during the three-year period. As expected, the coefficient on *Patents* is positive and significant in all nine models. In addition, new Ph.D.s are more likely to locate in MSAs with more higher education institutions and a higher proportion of highly educated residents. The coefficient on *PerBach*, or percent of the population with at least a bachelor's degree, is positive and significant in four of the models, and the coefficient on number of higher education institutions (*HighEd*) is also positive and significant in five of the nine models. It is important to acknowledge that the variables *HighEd* and *Patents* are likely to be related to the number of job opportunities available for Ph.D.s in a city, such that the results may reflect the fact that Ph.D.s are more likely to locate in a city with more potential jobs, as well as indicate a preference for cities with more universities and patents.[71]

Finally, the models include dummy variables specifying the region of the country in which the MSA is located. The South Central region is the benchmark in each model. The regions are included in the specification to try and capture any shared unobserved effects that are not explained by the other covariates. The coefficient on the Pacific region has the expected positive sign and is significant in all nine models. While we had no priors for the coefficients on the other regions, we find that the coefficients on the North Atlantic and North Central regions are consistently negative in the equations, but rarely significant. Furthermore, the results indicate that Ph.D.s generally prefer the shared unobserved characteristics in the Mountain region and the South Atlantic region to the South Central region, other things equal.

[71] The choice set selection process only partially controls for the influence of the number of employment opportunities in an MSA. This is because each city can only appear once in a choice set. As a result, cities with more employment opportunities are more likely to be selected into a Ph.D.'s choice set, but once selected, each city is implicitly assumed to offer an equal number of available jobs.

B. Conditional Logit Models with New Employees Results

A potentially important factor of the conditional logit models presented in Table 11 is that they include Ph.D.s with contractual obligations to previous employers. About 20% of all new Ph.D.s in the full sample had made a definite commitment to return to their previous employer. Recall, the model implicitly assumes that Ph.D.s consider numerous alternatives, and are observed in the city that maximizes utility. If a Ph.D.'s choice set is constrained by contractual obligations, then that Ph.D. may not be able to choose the city that offers them the highest utility. Thus, the models on city choice would not accurately represent the influence of amenities on location choice for these Ph.D.s. To ensure that the coefficients and willingness to pay estimates are not biased by the inclusion of Ph.D.s who may not have had full control over their choice of employment city, location choice models are estimated that exclude Ph.D.s with contractual obligations to a previous employer.[72]

The results from the "new employee" models are presented in Table 12. For purposes of comparison, the specification has not changed and the results from each model are reported in the same order as in Table 11. A comparison of the coefficient estimates indicates that the signs of the coefficients are not sensitive to the removal of Ph.D.s with contractual obligations to their previous employers. In fact, no significant coefficient changes signs when Ph.D.s with contractual obligations are removed from the analysis. However, the magnitudes and the statistical significance of the coefficients change considerably for some variables. Notably, the coefficient on private consumption is larger in the models that exclude Ph.D.s with contractual obligations, and the

[72] Initially, we also estimated separate models that excluded Ph.D.s who did not move to a new city. These results are not included in order to simplify the discussion, and because the results from these models were very similar to the results that exclude Ph.D.s returning to a previous employer.

coefficients on amenity variables are generally lower in absolute value. Thus, the estimates for implicit prices and willingness to pay will be more conservative when calculated from the models that exclude Ph.D.s with contractual obligations.

In order to assess the stability of parameters to the sample of Ph.D.s, Table 13 shows the variation of the coefficients across models in percentage terms. The percentage variation statistic, *PRange*, equals the difference between the largest and smallest coefficient estimate divided by the mean value of the coefficient. A lower value of *PRange* indicates more stability in the coefficients. It is evident from Table 13 that the coefficients from the new employee models are more stable than the coefficients from the models that include all Ph.D.s. The percentage ranges are smaller for 22 of the 30 variables, and are on average about 50% lower in the models that only include new employees. As a result of these considerations, the remainder of the analyses will focus exclusively on Ph.D.s who do not have contractual obligations to a previous employer.

C. Controlling for Observed Heterogeneity

Most previous applications of random utility models assume that consumers have homogeneous preferences for site attributes (Dahlberg & Eklof, 2003; Parsons & Kealy, 1992; Quigley, 1985). While this may not be an unreasonable assumption in some applications relating to recreational sites, individual preferences for city attributes are almost certainly characterized by some form of heterogeneity. For example, it is reasonable to expect that single individuals have a lower demand for education than people who are married with children. Similarly, preferences for diversity in a city likely differ between whites and non-whites. In order to understand how individual factors impact amenity preferences, as well as to provide more precise willingness to pay estimates, several individual characteristics are introduced into the specification.[73]

Although individual characteristics such as marital status or race may affect preferences for amenities, they cannot directly enter the model because any variable that is invariant among city alternatives will drop out of the model (see equation 6). Previous studies that control for preference heterogeneity do so either by estimating separate demands across socio-demographic characteristics (Boxall & Adamowicz, 2002; Cragg & Kahn, 1997), or by interacting individual characteristics with relevant city attributes (Chattopadhyay, 2000; Hauber & Parsons, 2000; Rolfe & Louviere, 2000). The latter method, herein referred to as the "hybrid" model, is more appropriate for this application because it allows us to account for heterogeneity across a larger array of observed characteristics.[74]

The hybrid model considers seven socio-demographic attributes that may influence the value of amenities. These include the Ph.D.'s age at the time of degree, and dummy variables indicating marital status, parental status, sector of employment, citizenship, race, and finally, an indicator of whether the Ph.D. has previously migrated to a new state. Bearing in mind that there are a great number of possible interaction terms between individual and MSA attributes, the models first consider interaction terms that one would expect to affect preferences *a priori*.[75] The intuitive interaction terms include: age, marital status, and the migration indicator with distance; parental status with

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[73] Rolfe and Louviere (2000) explain that the inclusion of socio-economic characteristics can significantly improve the accuracy of the coefficient estimates in discrete choice models.
[74] This is referred to as a "hybrid" model in some literature because it combines aspects of both the conditional and the multinomial logit models. It has also been referred to as an "interactive" random utility model (Massey, 2002).
[75] There are over 200 possible interaction terms between seven individual characteristics and thirty city attributes.

education attributes and violent crime rates; race with percent non-white; citizenship with percent foreign born; and finally, an indicator for industry with number of patents.[76]

The role of a Ph.D.'s sector of employment on their choice of city and amenity preferences is of particular concern in this application. Because the vast majority of postdoctoral appointments will not last for more than two years, postdocs may be more willing to accept a position in a city with lower quality amenities than Ph.D.s in more permanent positions. In addition, a postdoc's choice of city is largely driven by the quality of the available appointments in each city. Because the model does not include characteristics of each potential appointment, it implicitly assumes that the quality of available appointments is equal across cities. In reality, there is little doubt that a postdoc is more likely to choose a city that offers a more "rewarding" appointment, or one which will improve their future employment opportunities. To this extent, the preferences revealed by postdocs' city choices may be reflective of the preferences of the mentors with whom they desire to work.

Precisely how preferences for amenities differ across employment sectors, and thus how to interact sector dummies with city attributes, is not obvious. While interactions such as parental status with school variables are economically intuitive, whether or not preferences for an amenity such as July temperatures will vary across sectors is not evident. To determine how preferences vary across sector of employment, and thus which variables to interact with sector indicators, the coefficient on each attribute is separately tested for observed heterogeneity across sectors.

[76] We also initially considered additional interaction terms that could potentially affect preferences, such as age with the art and entertainment index or a faculty indicator with number of higher education institutions. However, these were not included in the final specification because they were not statistically significant in preliminary models.

The Wald tests are used to determine if sector interaction terms are needed on each variable. The Wald test is a flexible and useful method of testing for the equality of logit coefficients across groups (Liao, 2004). To implement the test, separate conditional logit models are estimated for two mutually exclusive sub-samples; in this case, postdocs versus Ph.D.s in industry and faculty. Next, a Wald statistics is calculated for each coefficient, equal to:

$$W_X = (\hat{\beta}_X^T - \sqrt{\hat{V}_X^T})^2 / (\hat{\beta}_X^P)^2 - \hat{V}_X^P) \tag{29}$$

where superscripts T and P refer to Temporary (postdocs) and Permanent (industry and faculty), respectively, $\hat{\beta}_X^T$ and $\hat{\beta}_X^P$ indicate the estimated coefficients for variable X, and $\hat{V}_X^T$ and $\hat{V}_X^P$ refer to the variances of these coefficient estimates. The test statistic is distributed chi-square with one degree of freedom, and the null hypothesis is equality of the coefficients. Rejection of the null for a coefficient indicates that observed heterogeneity exists in the attribute across sub-samples. The test is conducted on all coefficients of the three new employee conditional logit models estimated with 26 alternatives in the choice set (models 7-9 in Table 12).

The results from the Wald tests are presented in Table B.1 of the appendix. The table shows that the null hypothesis of coefficient equality is consistently rejected for seven variables: *JanSun, JulyRH, SupFund, ArtEnt, ComTime*, *PForBorn*, and *Patents.* Thus, these seven variables are interacted with an indicator of sector of employment in the hybrid specification.

Table 14 presents the definitions and descriptive statistics for relevant individual characteristics and interaction terms. As shown, the hybrid models introduce sixteen interaction terms into the specification. To facilitate the comparison, the hybrid models are estimated using the same nine choice set samples used previously. The results for all nine conditional logit hybrid models are presented in Table 15. These results are comparable to the results from the simple (non-hybrid) conditional logit models presented in Table 13.

Controlling for observed heterogeneity significantly improves the overall fit of the model, as measured by conventional statistics. Primarily, each model with interaction terms has a significantly lower log-likelihood value and a higher pseudo - R^2 statistic as compared to the same model without interaction terms.[77] These improvements are tested for significance using the Swait-Louviere log-likelihood ratio test.[78] The Swait-Louviere tests show that the improvements in the model are significant at the 5% level of confidence for all nine models, suggesting that the hybrid specifications more comprehensively explain the location choices of new Ph.D.s for these data.[79]

As indicated by Table 15, the inclusion of the interaction terms in the model captures a significant amount of heterogeneity in preferences across socio-demographic groups. Most of the coefficients on the interacted variables accord with prior expectations. For example, the three individual variables interacted with distance: *Age*, *Married*, and *SameC_Ph.D.*, each have a negative and significant coefficient in all nine models. These results suggest that the further a potential city is from Ph.D.s current locations, the less likely the city is chosen by older Ph.D.s, married Ph.D.s, or Ph.D.s who earned their doctorate in the same state in which they earned their college degree.

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[77] The pseudo R^2 in the conditional logit is similar to the adjusted R^2 of ordinary regressions except that the significance is assessed at lower values.
[78] The Swiat-Louviere test statistic is distributed chi-square and equals:
SW = -2(LL1-LL2), where LL1 and LL2 refer to the log-likelihood values from the models without and with interaction terms, respectively. The degrees of freedom equals the difference in the number of parameters in the model, in this case, sixteen.
[79] A common assessment tool in random utility modeling is to compare predicted choice probabilities to the actual probability. This test is only usable when the choice set contains the complete set of alternatives.

Furthermore, the coefficient on *distance* is positive and significant, suggesting that controlling for age, marital status, and previous migration behavior, Ph.D.s are actually more likely to choose a city that is geographically further from where they earned their doctorate.

Whether or not a Ph.D. is a parent has a large impact on preferences for amenities. Parental status is interacted with violent crime rates and the three education variables. The coefficient on *Par*VCrime* is negative and significant in all nine models, indicating that an increase in crime has a greater negative impact on the utility levels of Ph.D.s with children than Ph.D.s without children. Furthermore, the results indicate that parents prefer MSAs with a larger number of students per capita, and, consistent with earlier models, MSAs that have lower student expenditures, relative to Ph.D.s without children. The coefficients on *Par*PupTeach* are not significant at conventional levels, suggesting that preferences for pupil teacher ratios in school are relatively equal for parents and Ph.D.s without children.

The coefficients on *White*PNW* and *USCit*PFB* are negative and significant in all nine models, indicating, as expected, that whites and U.S. citizens are less likely to choose cities with higher amounts of diversity than are non-whites and foreign Ph.D.s, respectively.

The remaining seven interaction terms depict the relative preferences for amenities across sectors. The positive and significant coefficients on *Ind*Pats* suggest that industrial Ph.D.s are more likely to locate in cities with a larger number of utility patents, relative to Ph.D.s employed in an academic institution. The results also suggest that postdocs are more likely to locate in cities with more hours of January sunlight and larger amounts of art and entertainment enterprises than Ph.D.s in the other sectors. These coefficients are somewhat unexpected if one believes that because their employment situation is inherently temporary, postdocs are more willing to accept a position in a city with lower quality amenities. The positive coefficients on *Pdoc*CTime* indicate that the disutility from higher commute times is lower for postdocs than others. This result could be a measure of the "renters" effect; or that it is easier for postdocs to find an apartment close to campus than it is for others to find a home close to their employer. Furthermore, the results suggest that postdocs are less likely to locate in cities with higher amounts of superfund sites and higher July humidity, although the coefficients are not statistically significant in the majority of models. Finally, the negative coefficients on *Pdoc*PFB* suggest that postdocs have a lower likelihood of choosing cities with more foreign born, compared to industrial Ph.D.s and faculty.

In summary, the results suggest that observed heterogeneity is an important factor in city choice. Accounting for observed heterogeneity through the inclusion of the interaction terms improves the overall performance of the model. However, the coefficients from the conditional logit models may be biased if the models do not exhibit the IIA property. With this in mind, we now test for IIA violation in the conditional logit models.

D. Tests for IIA violation

Recall, the conditional logit models assume the data are consistent with the restrictive IIA property. Before proceeding with the less restrictive random utility models, we first test for violation of IIA in the conditional logit models. Hausman and

McFadden (1984) propose a specification test in which a model with a full set of choice alternatives is compared to a model with a restricted set of alternatives. Intuitively, if the conditional logit model exhibits the IIA property, then removing any alternative from the estimation will not significantly affect the ratio of probabilities associated with selecting a specific alternative. Thus, the results from a model estimated with the full set of alternatives should not change significantly when the same model is estimated with a restricted set of choice alternatives.

The Hausman-McFadden test statistic, Q, equals:

$$Q = [\beta_u - \beta_r]'[\Omega_r - \Omega_u]^{-1}[\beta_u - \beta_r] \tag{30}$$

where β_u and β_r refer to the vector of estimated coefficients, and Ω_u and Ω_r represent the variance covariance matrices from the unrestricted and restricted models, respectively. Rejection of the null hypothesis indicates that the likelihood ratios are not independent of irrelevant alternatives, or that the conditional logit models do not exhibit IIA. Thus, if the null is rejected, this is evidence that the estimates from the conditional logit models are not consistent or efficient. Alternatively, failure to reject the null indicates that the IIA property is not violated; hence implying that the conditional logit estimates are consistent but inefficient. The test is distributed χ^2, with the degrees of freedom equal to the number of covariates.

The Hausman-McFadden test statistics are reported in Table 16. The test statistics are conducted on each of the nine conditional logit models that exclude Ph.D.s with contractual obligations. As indicated by Table 16, the assumption of IIA cannot be rejected for any of the conditional logit models. Generally, the test statistics increase as the number of alternatives included in the equations decreases. This is to be expected because as the number of alternatives decrease, the effect of removing any single alternative will increase. Indeed, when the test was conducted on equations that include only four alternatives, we could reject the null of IIA at the 10% level of significance. However, the tests suggest that the data used for the conditional logit models satisfy IIA and that the estimates are consistent. This result (no rejection of IIA) is not common in the literature (Foster & Maurato, 2002; Mazzanati, 2003).

There are two logical explanations as to why the conditional logit models in this application exhibit the IIA property. The first is related to the determination of the choice set. Most previous applications randomly select alternatives into the choice set, or use the complete set of alternatives in the estimation. In this application, only alternative cities that were chosen by similar individuals (e.g. those considered to be competing for the same jobs) are selected into each individual's choice set. The objective of this choice set selection process was to decrease the number of irrelevant alternatives that are included in each Ph.D.'s choice set. The low Hausman-McFadden test statistics may reflect that this objective was achieved.

Furthermore, the model will likely not exhibit the IIA property if the unobservable characteristics of MSAs are correlated within regions. A common method for maintaining IIA when this is the case is to cluster alternatives by region, and estimate a nested logit that separately models the choice of region and alternatives within a region (Knapp *et al.*, 2001). An alternative method to capturing correlation between regions, which is used here, is to include region specific dummies (List & Co, 2000; Parsons & Massey, 2003).[80]

[80] The Hausman test statistics significantly increase when the specification does not include region specific dummies, but are not high enough to reject IIA at the 10% level of significance.

Although the tests suggest the conditional logit models do not violate the IIA property, it is still desirable to estimate choice probability with less restrictive models. The Hausman-McFadden test statistics are sensitive to the specific number of alternatives included in the choice set, as well as the specific alternative that is removed from the unrestricted choice set. Thus, the test is particularly prone to Type I errors. If the IIA property is exhibited in the conditional logit models (and the test statistics are accurate), estimation of the less restrictive models should only lend validity to the previous results.

E. Nested Logit Model Results

In this section we estimate the nested logit model discussed in Chapter 2, Section C. The nested logit framework partitions MSAs into groups (or nests) by sector of employment and then estimates the probability an individual will choose a sector of employment, in addition to the probability of choosing a city within a sector. The IIA property is still assumed to hold within nests, but is not required across nests.

The appropriateness of this nesting structure is unknown prior to estimation. Even if a nesting structure seems intuitively suitable, it cannot be known whether or not the model will satisfy certain requirements for consistency with utility maximization until the model has been estimated and tested. Specifically, in order for the model to remain consistent with utility theory, the coefficient on the inclusive value (IV) must take on a value between zero and one (Ben-Akiva & Lerman, 1985; McFadden, 1978).[81]

To test the validity of the sector-city nesting structure, we first estimate a sequential nested logit model that constrains the parameter on the inclusive value to be equal across

[81] Borsch-Supan (1990) has shown that in some cases, the coefficient on the inclusive can lie above one and still be consistent with utility theory.

nests. Sequential estimation is consistent but inefficient relative to simultaneous (FIML) estimation (Amemiya, 1978; Ben-Akiva & Lerman, 1985). Procedurally, sequential estimation of the nested logit model involves first calculating the inclusive values (log-sum utility) for each sector, using the estimated coefficients from the conditional logit models on city choice. The inclusive value equals the natural log of the exponentiated sum of utilities from all cities in a sector, or:

$$IV_i \;= \ln\left(\sum_{j=1}^{J} e^{\hat{\beta}\; Zj+\hat{\Psi}\; C_{ij}}\right) \tag{31}$$

where $\hat{B}$ and $\hat{\psi}$ represent the estimated coefficients from the lower level nest, in this case, the conditional logit models on the choice of city. Next, a standard logit probability is estimated for the choice of nest (sector), with the inclusive values entering the equation as an explanatory variable. The probability individual *i* choose sector *k* equals:

$$P(i, \text{sector } k) \;= \frac{e^{\phi^k Xi'+\delta^k P_S+o^k IV_i^k}}{\sum_{k=1}^{K} e^{\phi Xi'+\delta P_S+oIV_i}} \tag{32}$$

where X_i, represents various individual characteristics and P_s refers to characteristics of the Ph.D. granting institution. Table B.2 of the appendix gives definitions and descriptive statistics for all individual and institutional characteristics used in the model. The individual and institutional variables are interacted with alternative specific constants (ASCs) for both the academic and industrial sectors in the model.

Table B.3 in the appendix presents results from two sector choice logits, NL1 and NL2. The sector choice models are identified for two specifications of the city choice logit models: model (1) and model (9) of the “new employee” models (Table 12). In the first model (NL1), the inclusive values are calculated using the coefficients from model

(1) of the city choice estimation on new employees (Table 12, Column 2). The second model (NL2) obtains the inclusive values from coefficients in model (9) of the city choice model (Table 12, Column 9).

As indicated in Table B.3, the coefficients on the inclusive value are statistically significant at the 99% level, but consistently lie outside of the unit range, and thus outside of the theoretically acceptable range. Specifically, in NL1 the IV coefficient (*IncVal*) equals - 0.32, and in NL2 *IncVal* equals -0.28.[82] These results conflict with utility maximization theory because they imply that the greater the expected utility level in a sector, the lower is the likelihood that the sector will be chosen by Ph.D.s.

There are two possible explanations for the illogical outcome of the nested model, both relating to the information captured by the inclusive values. Recall, the inclusive value estimates the systematic expected utility of the complete set of alternatives in each sector, and brings information from the lower nest (city choice) to the upper nest (sector choice) by measuring the shared unobserved attributes common to alternatives in each nest. In this application, each nest includes at least 161 different MSAs, and casual observation indicates that the full set of MSAs within each nest generally have very little in common with one another. This can be problematic in the nested model because the shared unobserved effects and associated correlations among alternatives within a nest (cities within a sector) may be so weak that they do not influence an individual's choice of nest (sector). In other words, with such a wide range of cities in each sector, the inclusive values may not sufficiently capture the unobserved sources of correlation across the full set of cities in a sector.

[82] Several other specifications for the nested logit were estimated, such as including additional individual variables or only including the inclusive values as explanatory variables. Because the IV parameter consistently remained negative and statistically significant these results are not reported.

Furthermore, in most nested logit applications, each alternative is a member of only one nest, whereas is in this application, a city almost always appears in more than one nest.[83] In fact, approximately 75% of all observed MSAs are members of multiple nests, representing the location choices of over 90% of Ph.D.s.[84] When such a large proportion of the cities are potential alternatives in more than one sector, there is likely to be little variation in expected utility across sectors.

To explore the effects of overlapping nests, we estimate the same model using a generalized nested logit (GNL). The GNL may improve the results by allowing the alternatives to have variable influence on each nest in which it appears. The GNL is virtually equivalent to the standard nested logit except it includes fractional allocation parameters that reflect the degree to which an MSA is a member of each sector. The allocation parameters are proportional to the percentage of Ph.D.s observed in an MSA in each sector. [85]

The results from two GNLs (GNL1 and GNL2) are presented in Tables A8 of the appendix. For purposes of comparison, the models are estimated on the same set of explanatory variables, and the inclusive values are calculated using the same sets of coefficients as in the nested logit models discussed above (models 1 and 9 in Table 12). As shown in Table B.4, the results from the GNL estimation are very similar to those from the standard NL estimation. Of primary importance, the coefficient on the inclusive

[83] See Moshe Ben-Akiva and Bierlaire (1999), Vovsha (1997), or Wen and Koppelman (2001) for examples of papers that apply the nested logit with overlapping nests.
[84] Specifically, of the 291 observed MSAs, 142 are chosen by at least one Ph.D. in all three sectors, and 211 are chosen by Ph.D.s in more than one sector.
[85] In an application to transportation choice Wen and Koppelman (2001) estimate both a GNL and nested logit and find the GNL to be statistically superior to the standard nested logit model.

value remains negative and statistically significant in both GNL models. Specifically, the IV parameters (*IncVal*) equal -3.07 and -0.85 in GNL1 and GNL2, respectively.

Judging from the results of both the standard nested logit and the generalized nested logit models, it is evident that the proposed nesting structure is not an appropriate characterization of the migration decisions of new Ph.D.s for these data. Thus, we surmise that although the nesting structure is intuitively appealing, it does not improve the accuracy of the parameters from the conditional logit estimation, and thus will not be used not be used in the calculation of implicit prices or willingness to pay.

F. Mixed Logit Model Results

This section presents results from the mixed logit random utility model discussed in Chapter 2, Section 4. The mixed logit is less restrictive than the conditional logit model because it does not require the IIA property and allows for unobservable heterogeneity in preferences. Although the conditional hybrid models estimated in Section 3 of this chapter control for observed heterogeneity across socio-demographic groups, unobserved heterogeneity among individuals with the same observed characteristics may continue to affect the coefficient estimates. Several papers have shown that unobservable heterogeneity can be a significant factor in coefficient estimates even after the model has controlled for observed heterogeneity (Massey, 2002; Morey & Rossmann, 2003; Revelt & Train, 1998; Rouwendal & Meijer, 2001).

The mixed logit models allow the coefficients for a set of attributes to randomly vary across individuals according to a specific distribution. Although the mixed logit exhibits less stringent properties than the conditional logit, a number of assumptions must be made regarding the specific structure of heterogeneity over the population. Namely, in any mixed logit application, the researcher determines the appropriate coefficients to distribute (specify as random), as well as make assumptions regarding the appropriate mixing distribution for each distributed coefficient (Hensher & Greene, 2001). Furthermore, while the mixed logit model can detect the presence of heterogeneity, it cannot identify the sources or causes of it (Boxall & Adamowicz, 2002).

Before determining which of the parameters to distribute, one must consider a number of both practical and theoretical issues. Unobserved heterogeneity may affect preferences for any attribute, such that all attributes should be considered potential candidates for distribution prior to estimation. However, only those variables for which the population has a significant amount of unobserved heterogeneity in preferences need to be distributed. On practical grounds, as the number of distributed parameters increases, identification can become very difficult, and computing time needed to obtain model convergence can increase dramatically.[86] In addition, allowing both the coefficient on private consumption (price or cost in other applications) and the coefficients on attributes to vary makes the calculation and interpretation of willingness to pay measures complex (Hensher & Greene, 2001; Revelt & Train, 1998). As a result, most previous empirical applications have chosen to either distribute the coefficient on income (Hess *et al.*, 2004; Layton & Brown, 2000; Nalder & Morrison, 2004) or a set of coefficients on non-income related variables (Parsons & Massey, 2003; Revelt & Train, 1998; Rouwendal & Meijer, 2001), but applications rarely choose to distribute both.[87]

[86] For example, a mixed logit model with fifteen random parameters can take more than three days to converge (or report a lack of convergence), while the same mixed logit with only one random parameter generally only takes about two hours to converge.
[87] Two known exceptions include (Brownstone & Train, 1999; Train, 1997).

In light of these considerations, we test for the presence of unobserved heterogeneity in each attribute by deriving the standard deviation of the coefficient distribution for each variable in separate models.[88] The derived standard deviation of a coefficient distribution measures the extent of variation in preferences over the population, or the degree that unobserved heterogeneity affects preferences for an attribute (see section 4, Chapter 2). Put simply, a derived standard deviation that is not significantly different from zero indicates that preferences for an attribute are relatively constant across the population, and that the coefficient need not be distributed. Thus, a coefficient is distributed in the final specification if the derived standard deviation of the distribution was significantly different from zero at the 10% level or better in preliminary models. Conversely, if the derived standard deviation of the coefficient distribution was not significant at the 10% level in the preliminary equations, then the coefficient is held constant across individuals.

The preliminary estimations indicated that the coefficient on composite consumption did not have a statistically significant derived standard deviation, suggesting that there is not unobserved heterogeneity in preferences for composite consumption in the population of Ph.D.s. Thus, the model only distributes the coefficients on a set of non-income related variables for which the derived standard deviation of the distribution are significantly different from zero. The following five variables were found to have a

[88]The terminology can be confusing here. There are two types of standard deviations for a coefficient in a mixed logit: the derived standard deviation, which only exist for random parameters, and the classical standard errors that exist for all (random and nonrandom) parameters. When discussing the presence of heterogeneity, we are referring to the derived standard deviation of the parameter distributions.

statistically significant derived standard deviation: *JanSun, JanTemp, StudExp, Pnonwhite*, and *Patents*.[89]

The choice of a distribution for a coefficient is dependent on how one expects the structure of tastes for a particular attribute to vary over the population. Any coefficient could theoretically be specified with any distribution (e.g., normal, uniform, triangular, etc.); however, almost all previous applications choose to distribute coefficients with a normal or a lognormal distribution. The advantage of the lognormal distribution is that the coefficients are constrained to have the same sign for all individuals, whereas the standard normal distribution allows for both positive and negative coefficients (Train, 1997). The variables with random coefficients are all attributes that may be desirable to some but not preferred by others.[90] Thus, the random coefficients on these attributes are specified to follow a normal distribution.

The random coefficient estimates are based on 200 Halton draws in all models. Halton draws, or "intelligent" draws, are preferred to standard random draws because they reduce the simulation variance and enable faster estimation (Train, 1999). Unlike random draws, the Halton draws use information from previous draws of the coefficient to ensure better coverage over the full range of simulated probabilities. Bhat (2003) has shown that a mixed logit model estimated with 100 Halton draws requires more than 2,000 random draws in order to achieve the same level of accuracy.

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[89]The coefficient on *distance* was also found to have significant unobserved heterogeneity in some preliminary models. However, it is held constant in the final specification because including it as a random coefficient made identification difficult and the interpretation of distance is not central to estimates of amenity values.

[90] This is as opposed to the coefficient on a variable like private consumption, for which all individuals can be assumed to prefer more of to less.

The coefficient estimates for the mixed logit models are presented in Table 17. For ease of interpretation, the models are only reported for the three draws on choice set size 26 (models 7-9 in previous tables), using the same set of explanatory variables as in the conditional logit models. The results for random coefficients are reported in terms of the mean coefficient and the standard deviation. The results for all coefficients are reported with an indicator of whether they are significant at the 1%, 5%, or 10% level. The table also reports the derived standard deviation value, indicated by the prefix "STD", and an indicator of the level of significance of the derived standard deviation. Table 17 presents results from both the simple specifications (columns 2-4) and the hybrid specifications (columns 5-7). Note that the hybrid mixed logit models allow the coefficients on the relevant interacted variables to be random in addition to the non-interacted variables. Thus, the hybrid mixed logit controls for observed and unobserved (random) heterogeneity in preferences, while the simple specification only accounts for unobservable heterogeneity in preferences.

The mixed logit model results are qualitatively similar to those from the conditional logit models. In fact, all but two of the thirty coefficients in the simple specification (Spec 1) have the same sign in the mixed logit as in the previous models. However, several notable differences arise. First, the population mean coefficient values are not statistically significant for all of the distributed variables except for *StudExp* in the simple specification. However, the derived standard deviations are statistically significant for *JanTemp*, *StudExp*, *Pnonwhite,* and *Patents*. This suggests that preferences for these variables are not homogenous across the population. Furthermore, the derived standard deviation is larger than the mean coefficient values for each of the five attributes with random coefficients, which indicates that there are both positive and negative preferences in the population for all five variables. Thus, while the mean values of the random coefficients are not significantly different from zero, this does not imply that the attribute has no effect on the likelihood of choosing a city for all Ph.D.s.

The coefficients from the mixed logit models with interaction terms are also very similar to those from the hybrid specification of the conditional logit models. The model performs considerably better than the mixed logit with the simple specification, at least in terms of the significance levels of the mean random coefficients.[91] Whereas only the mean coefficient value for *Studexp* is statistically significant in the Specification 1 of the mixed logit, the mean coefficient values are statistically significant for *Studexp, Pnonwhite*, and the interacted variables *White*Pnonwhite, Par*Studexp* and *Ind*Pats.* The derived standard deviations of the random coefficients are generally significant as well. Specifically, only the estimated standard deviation for the variables *Par*Studexp* and *Pnonwhite* are not significantly different from zero.

The hybrid specifications of the mixed logit models provide a more comprehensive recognition of the degree and type of heterogeneity in preferences than the other models. The case of preferences for the percentage of minority residents *(Pnonwhite)* in an MSA serves as a good example. In specification 1 of the mixed logit, the mean coefficient on *Pnonwhite* is positive and the derived standard deviation is statistically significant. This suggests that on average Ph.D.s prefer MSAs with higher percentages of minorities, and that the preference for this attribute significantly varies across the population of Ph.D.s. In the hybrid mixed logit with interaction terms, the

[91] The coefficient is *JanSun* is held constant in the hybrid specifications of the mixed logit because the derived standard deviation is not statistically significant in the simple specification.

mean coefficient on *Pnonwhite* is positive and the derived standard deviation is not significantly different from zero. Furthermore, the mean coefficient on *White*Pnonwhite* is negative and the derived standard deviation is statistically significant. One can tell a much richer story regarding how preferences for the percentages of minorities in an MSA vary across the population of Ph.D.s using these results. The positive mean coefficient on *Pnonwhite* (not interacted) suggests that on average Ph.D.s prefer MSAs with higher percentages of minorities. The fact that the derived standard deviation on the coefficient is not significantly different from zero suggests that preferences for *Pnonwhite* are relatively constant across the population of minority Ph.D.s. In addition, the negative and significant mean coefficient on the interaction term, *White*Pnonwhite*, indicates that white Ph.D.s have systematically lower preferences for cities with higher percentages of minorities. Finally, the statistically significant derived standard deviation on the interacted coefficient suggests that that this preference varies across the population of white Ph.D.s.

The overall performance of the mixed logit models relative to the conditional logit models were also tested using the log-likelihood ratio test. The tests suggest that both the hybrid and the simple mixed logit models better explain location choices of Ph.D.s for these data, relative to the conditional logit models with the same specification, at the 5% level.[92] Based on these results, we can conclude that the mixed logit model not only uncovers a significant amount of unobservable heterogeneity in preferences, but that accounting for this heterogeneity improves the overall performance of the model. This

[92] Note that here we are testing the model performance of the mixed logit models relative to the conditional logit model with the same specification, not the performance of the mixed logit specifications to one another.

result generally accords with the conclusions of the majority of research that compares mixed logit models to conditional logit model.[93]

G. Summary

This chapter has explored the impact of city attributes on Ph.D. utility through the estimation of numerous random utility models. While the qualitative interpretations of the coefficients are similar across models, several important differences have been revealed. The main findings relating to the estimation strategy can be summarized as follows.

- The results are more stable across models, and the coefficient standard errors are smaller when Ph.D.s' choice sets include a larger number of alternative cities.
- Ph.D.s who have contractual obligations to a previous employer may have biased utility estimates if their commitment prevents them from choosing the city they would otherwise prefer. Although the results cannot detect this theoretical bias, the coefficients are more stable and consistent in the models that are restricted to new employees.
- Accounting for heterogeneity in preferences is an important feature of the model. The introduction of interaction terms into the specification not only significantly improves the parametric fit of the model, but also shows how preferences for city attributes differ across observable characteristics. Specifically, preferences vary according observable characteristics for the following ten city attributes: January sunlight, July humidity, art and entertainment enterprises, violent crime rates,

[93] Exceptions are rare but do exist. For example, Birol *et al.* (2004) and Dahlberg and Eklof (2003) find that the mixed logit and the conditional logit models perform equally well.

number of students, student expenditures, commute times, percent nonwhite, percent foreign born, and number of patents.

- The Hausman McFadden tests do not detect IIA violation in the conditional logit models, suggesting that the coefficient estimates from the conditional logit models are consistent.
- The sector-city nested logit model, although intuitively appealing, does not appropriately characterize city choice for these data, as assessed by the negative coefficient on the inclusive value. This is likely the result of the large degree of non-exclusivity of cities across nests.
- The coefficient estimates from the mixed logit model are very similar to the conditional logit model. Log-likelihood ratio tests suggest that the mixed logit models perform better than the conditional logit models. Furthermore, the mixed logit models detect unobservable heterogeneity in preferences for January temperature, student expenditures, percent nonwhite, and number of patents. The results from the hybrid mixed logit suggest that unobserved heterogeneity affects preferences for these attributes even after controlling for observed characteristics of Ph.D.s.

Based on the above considerations, the preferred results from the conditional and mixed logit models are used in the next chapter to estimate and compare willingness to pay for various amenities.

Table 11

Coefficient Estimates from Simple Conditional Logit:
Full Sample

	SAMPLE 1: Full Sample (N=22,666)								
	Choice Set Size = 6			Choice Set Size = 11			Choice Set Size = 26		
Variable	Model 1 (Draw 1)	Model 2 (Draw 2)	Model 3 (Draw 3)	Model 4 (Draw 1)	Model 5 (Draw 2)	Model 6 (Draw 3)	Model 7 (Draw 1)	Model 8 (Draw 2)	Model 9 (Draw 3)
CompCons	0.00006[C]	0.00005[B]	0.00004[B]	0.00006[C]	0.00008[C]	0.00008[C]	0.00013[C]	0.00013[C]	0.00013[C]
Distance	-1.163[C]	-1.160[C]	-1.164[C]	-1.2246[C]	-1.218[C]	-1.212[C]	-1.2777[C]	-1.2749[C]	-1.2744[C]
JanSun	-0.0006[B]	-0.0010[C]	-0.0003	-0.0003	-0.0007[B]	-0.0008[B]	-0.0007[B]	-0.0006[B]	-0.0006[B]
JanTemp	0.0089[C]	0.0077[C]	0.0079[C]	0.0090[C]	0.0100[C]	0.0089[C]	0.0104[C]	0.0101[C]	0.0099[C]
JulRH	-0.0051[C]	-0.0054[C]	-0.0045[C]	-0.0056[C]	-0.0063[C]	-0.0054[C]	-0.0089[C]	-0.0091[C]	-0.0091[C]
JulTemp	-0.0077	-0.0086[A]	-0.0087[A]	-0.0095[B]	-0.0133[C]	-0.0080[A]	-0.0169[C]	-0.0170[C]	-0.0166[C]
PWater	0.0009	0.0009	0.0009	0.0004	-0.0008	-0.0007	-0.0020[B]	-0.0015[A]	-0.0014
Coast	0.0171	0.0467	0.0344	0.0809[C]	0.0553[B]	0.0737[C]	0.1176[C]	0.1106[C]	0.1043[C]
Vcrime	-0.00007	-0.00006	-0.00007	0.00002	-0.00004	-0.000005	-0.00002	-0.00001	-0.00003
Parkacre	-0.0014	-0.0016[A]	-0.0011	0.0001	-0.00124	-0.00076	-0.00114	-0.00137[A]	-0.00123
BadAQ	-0.0025[B]	-0.0029[C]	-0.0029[C]	-0.0015	-0.0033[C]	-0.0030[C]	-0.0029[C]	-0.0028[C]	-0.0031[C]
Supfund	0.0016	0.0015	0.0018[A]	0.0013	0.0025[C]	0.0023[B]	0.0024[C]	0.0028[C]	0.0028[C]
Art_Ent	-0.0009	-0.0002	-0.0012	-0.0026[C]	-0.0013	-0.0015[A]	-0.0020[B]	-0.0015[A]	-0.0016[B]
Studexp	-0.0199	-0.0294[A]	-0.0289[A]	-0.0140	-0.0198	-0.0109	-0.0213	-0.0265[A]	-0.0258[A]
PupTeach	-0.0046[A]	-0.0047[A]	-0.0038	-0.0021	-0.0040	-0.0032	-0.0050[B]	-0.0039	-0.0038
NStudnts	-0.0029	-0.0006	-0.0029	-0.0017	-0.0009	0.0029	-0.0029	-0.0001	-0.0007
Comtime	-0.0053	-0.0066[A]	-0.0024	-0.0087[C]	-0.0078[B]	-0.0076[B]	-0.0103[C]	-0.0103[C]	-0.0085[B]
MSASize	0.0123[C]	0.0139[C]	0.0095[B]	0.0082	0.0131[C]	0.0087[B]	0.0121[C]	0.0122[C]	0.0110[C]
PopDens	0.0049	0.0014	0.0013	-0.0139	0.0100	0.0012	-0.0122	-0.0094	-0.0151
PerDem	0.0012[A]	0.0006	0.0009	0.0017[C]	0.0005	0.0009	0.0013[B]	0.0010	0.0011[A]
PerBach	0.0011	0.0005	-0.0002	0.0036[B]	0.0014	0.0020	0.0031[B]	0.0037[B]	0.0035[B]
Pnonwhite	0.0004	0.0028	0.0020	0.0007	0.0009	0.0010	0.0022	0.0023	0.0022
Pforborn	0.0054[B]	0.0052[B]	0.0046[B]	0.0064[C]	0.0060[C]	0.0057[C]	0.0083[C]	0.0080[C]	0.0088[C]

HighEd	0.0011	0.0007	0.0010	0.0037[B]	0.0031[A]	0.0029[A]	0.0085[C]	0.0078[C]	0.0081[C]
Pats	0.0007[C]	0.0010[C]	0.0009[C]	0.0012[C]	0.0013[C]	0.0013[C]	0.0020[C]	0.0021[C]	0.0020[C]
NorthAtl	-0.021	0.018	-0.002	-0.0129	-0.0561	-0.0454	-0.0785	-0.0577	-0.0600
SouthAtl	0.050	0.067[A]	0.046	0.0057	0.0535	0.0562	0.0876[B]	0.0856[B]	0.0913[B]
NorthCen	-0.024	-0.037	-0.012	-0.0632	-0.0545	-0.0386	-0.0485	-0.0483	-0.0377
Mount	0.183[C]	0.127[B]	0.159[B]	0.0656	0.1191[B]	0.1610[C]	0.0438	0.0123	0.0205
Pacific	0.392[C]	0.388[C]	0.375[C]	0.3709[C]	0.2960[C]	0.3653[C]	0.2626[C]	0.2426[C]	0.2546[C]
Log-Likeli	-33766	-33798	-33799	-45247	-45321	-45375	-60575	-60594	-60583
Pseudo R^2	0.169	0.168	0.168	0.167	0.166	0.165	0.180	0.179	0.180

[A] Indicates the coefficient is significantly different from zero at the 10% level of significance.
[B] Indicates the coefficient is significantly different from zero at the 5% level of significance.
[C] Indicates the coefficient is significantly different from zero at the 1% level of significance.

Table 12

Coefficient Estimates from Simple Conditional Logit:
New Employees

	SAMPLE 2: Ph.D.s without Contractual Obligation to Previous Employers (N= 18,795)								
	Choice Set Size = 6			Choice Set Size = 11			Choice Set Size = 26		
Variable	Model 1 (Draw 1)	Model 2 (Draw 2)	Model 3 (Draw 3)	Model 4 (Draw 1)	Model 5 (Draw 2)	Model 6 (Draw 3)	Model 7 (Draw 1)	Model 8 (Draw 2)	Model 9 (Draw 3)
CompCons	0.00008[C]	0.00007[C]	0.00006[C]	0.00008[C]	0.00011[C]	0.00011[C]	0.00015[C]	0.00016[C]	0.00016[C]
Distance	-0.999[C]	-0.996[C]	-0.996[C]	-1.0447[C]	-1.038[C]	-1.034[C]	-1.077[C]	-1.073[C]	-1.073[C]
JanSun	-0.0008[B]	-0.0011[C]	-0.0007[A]	-0.0005	-0.0009[C]	-0.0010[C]	-0.0008[B]	-0.0007[B]	-0.0007[B]
JanTemp	0.0075[C]	0.0065[C]	0.0069[C]	0.0076[C]	0.0086[C]	0.0073[C]	0.0087[C]	0.0085[C]	0.0081[C]
JulRH	-0.0041[C]	-0.0047[C]	-0.0040[C]	-0.0047[C]	-0.0055[C]	-0.0045[C]	-0.0082[C]	-0.0084[C]	-0.0083[C]
JulTemp	-0.0056	-0.0066	-0.0064	-0.0061	-0.0113[B]	-0.0060	-0.0147[C]	-0.0157[C]	-0.0135[C]
PWater	-0.0003	-0.0005	-0.0004	-0.0009	-0.0022[B]	-0.0023[B]	-0.0031[C]	-0.0029[C]	-0.0026[C]
Coast	0.0375	0.0660[B]	0.0507	0.1019[C]	0.0832[C]	0.1010[C]	0.1348[C]	0.1391[C]	0.1284[C]
Vcrime	-0.00008	-0.00006	-0.00008	-0.00001	-0.00004	-0.00001	-0.00004	-0.00002	-0.00005
Parkacre	-0.0018[A]	-0.0019[A]	-0.0014	-0.0002	-0.0016[A]	-0.0012	-0.0017[A]	-0.0019[A]	-0.0018[A]
BadAQ	-0.0033[C]	-0.0033[C]	-0.0031[C]	-0.0017	-0.0036[C]	-0.0033[A]	-0.0032[A]	-0.0031[A]	-0.0036[A]
Supfund	0.0011	0.0008	0.0011	0.0004	0.0016	0.0016	0.0017[A]	0.0021[B]	0.0021[B]
Art_Ent	0.0003	0.0007	-0.0003	-0.0019[B]	-0.0007	-0.0007	-0.0012	-0.0006	-0.0008
PupTeach	-0.0088[C]	-0.0089[C]	-0.0093[C]	-0.0134[C]	-0.0095[C]	-0.0076[C]	-0.0102[C]	-0.0090[C]	-0.0093[C]
Studexp	-0.0259	-0.0268	-0.0281[A]	-0.0076	-0.0226	-0.0109	-0.0254[A]	-0.0298[A]	-0.0275[A]
NStudnts	-0.0008	0.0001	-0.0019	-0.0029	-0.0004	0.0014	-0.0044	-0.0007	-0.0013
Comtime	-0.0027	-0.0037	-0.0019	-0.0068[A]	-0.0066	-0.0063	-0.0082[B]	-0.0088[B]	-0.0064[A]
MSASize	0.0121[B]	0.0121[B]	0.0072	0.0048	0.0116[C]	0.0078[A]	0.0105[B]	0.0117[C]	0.0094[B]
PopDens	-0.0012	-0.0102	-0.0111	-0.0318[B]	-0.0026	-0.0110	-0.0253[A]	-0.0185	-0.0299[B]
PerDem	0.0010	0.0002	0.0009	0.0018[B]	0.0004	0.0008	0.0014[B]	0.0009	0.0011
PerBach	0.0017	0.0007	0.0003	0.0038[B]	0.0021	0.0022	0.0035[B]	0.0044[B]	0.0038[B]
Pnonwhite	0.0008	0.0026	0.0023	0.0009	0.0013	0.0011	0.0029[A]	0.0030[A]	0.0028[A]
Pforborn	0.0056[B]	0.0059[B]	0.0059[B]	0.0081[C]	0.0069[C]	0.0070[C]	0.0094[C]	0.0084[C]	0.0099[C]

HighEd	0.0018	0.0019	0.0024	0.0055[C]	0.0044[B]	0.0039[B]	0.0097[C]	0.0086[C]	0.0095[C]
Pats	0.0009[C]	0.0012[C]	0.0011[C]	0.0014[C]	0.0015[C]	0.0015[C]	0.0022[C]	0.0024[C]	0.0022[C]
NorthAtl	0.067	0.097	0.082	0.0762	0.0466	0.0459	0.0237	0.0417	0.0420
SouthAtl	0.113[B]	0.131[C]	0.120[C]	0.0799[A]	0.1341[C]	0.1342[C]	0.1686[C]	0.1611[C]	0.1755[C]
NorthCen	0.028	0.026	0.055	0.0103	0.0157	0.0270	0.0242	0.0198	0.0365
Mount	0.207[C]	0.170[B]	0.211[C]	0.1204[A]	0.163[C]	0.216[C]	0.064	0.037	0.059
Pacific	0.428[C]	0.441[C]	0.426[C]	0.4391[C]	0.3612[C]	0.4194[C]	0.3197[C]	0.2933[C]	0.3318[C]
Log-Likeli	-28817	-28844	-28867	-38471.9	-38532	-38569	-51283	-51280	-51285
Pseudo R^2	0.144	0.143	0.143	0.146	0.145	0.144	0.163	0.163	0.163

[A] Indicates the coefficient is significantly different from zero at the 10% level of significance.
[B] Indicates the coefficient is significantly different from zero at the 5% level of significance.
[C] Indicates the coefficient is significantly different from zero at the 1% level of significance.

Table 13

Percent Ranges of Coefficients across Simple Conditional Logit Models

	ALL Ph.D.S (N=22,666)					New Employees (N=18,795)			
Variable	PRange All Csets	PRange Cset=6	PRange Cset=11	PRange Cset=26		PRange All Csets	PRange Cset=6	PRange Cset=11	PRange Cset=26
CompCons	1.46	0.27	1.18	0.02		1.17	0.24	0.83	0.04
Distance	0.096	0.003	0.047	0.003		0.074	0.003	0.048	0.0004
JanSun	1.16	1.05	0.87	0.19		0.73	0.49	0.61	0.10
JanTemp	0.29	0.15	0.12	0.05		0.28	0.15	0.17	0.07
JulRH	0.71	0.17	0.31	0.03		0.82	0.17	0.39	0.02
JulTemp	0.91	0.12	0.73	0.03		1.37	0.16	1.21	0.14
PWater	14.06	0.10	3.26	0.37		2.11	0.41	1.78	0.16
Coast	1.50	0.90	0.52	0.12		1.14	0.55	0.49	0.08
Vcrime	3.27	0.22	13.35	0.28		2.08	0.27	3.00	0.85
Parkacre	1.66	0.37	2.41	0.18		1.24	0.28	1.58	0.11
BadAQ	0.58	0.17	0.62	0.11		0.58	0.07	0.62	0.17
Supfund	0.74	0.17	0.60	0.17		1.25	0.31	1.02	0.24
Art_Ent	1.31	1.21	0.33	0.31		3.89	4.18	0.58	0.65
PupTeach	0.92	0.21	0.86	0.30		0.37	0.05	0.33	0.12
Studexp	0.85	0.36	0.63	0.21		0.77	0.08	0.84	0.16
NStudnts	6.65	1.08	5.14	2.24		3.40	2.42	2.90	1.73
Comtime	1.07	0.88	0.05	0.19		1.23	0.66	0.18	0.30
MSASize	0.47	0.38	0.44	0.10		0.72	0.47	0.80	0.23
PopDens	11.35	1.43	4.03	0.47		1.98	1.31	1.57	0.47
PerDem	0.90	0.73	0.97	0.25		1.38	1.06	1.23	0.38
PerBach	1.87	2.69	1.01	0.19		1.64	1.55	0.68	0.24
Pnonwhite	2.37	1.43	4.08	0.02		1.94	0.99	2.92	0.04
Pforborn	0.68	0.17	0.25	0.10		0.59	0.06	0.08	0.16
HighEd	2.14	0.41	1.16	0.09		1.59	0.28	0.65	0.11
Pats	1.26	0.26	0.78	0.06		1.12	0.20	0.66	0.08
NorthAtl	2.76	29.46	1.10	0.32		1.27	0.37	0.55	0.51
SouthAtl	2.05	0.38	2.90	0.07		0.95	0.15	0.79	0.09
NorthCen	1.60	1.03	0.71	0.24		2.37	0.80	2.52	0.62
Mount	1.56	0.36	0.40	0.91		1.25	0.21	0.30	0.49
Pacific	0.51	0.04	0.32	0.08		0.48	0.03	0.28	0.12

Table 14

Individual Variable Definitions, Interaction Terms, and Summary Statistics

Individual Variables	*Definition*	*Mean*	*Std Dev*
Age	Age of individual at the time of Ph.D.	32.7	5.4
Married	Dummy variable indicating whether or not Ph.D. is married	0.4	0.49
SameC_Ph.D.	Dummy variable indicating whether or not a Ph.D. was went college and earned in their Ph.D. in the same state	0.19	0.39
Parent	Dummy variable indicating whether or not Ph.D. has a child	0.22	0.42
White	Dummy variable indicating whether or not a Ph.D. is Caucasian	0.62	0.48
USCit	Dummy variable indicating whether or not a Ph.D. is a US Citizen	0.62	0.48
Industry	Dummy variable indicating whether or not a Ph.D. has definite plans for employment in industry	0.39	0.49
Postdoc	Dummy variable indicating whether or not a Ph.D. has definite plans for employment in a postdoctoral appointment	0.45	0.50
Interacted Variable Names	*Interaction*	*Mean*	*Std Dev*
Age*Dist	Age*Distance	213	25.2
Marr*Dist	Married*Distance	0.35	0.7
C_Ph.D.*Dist	SameC_Ph.D.*Distance	0.10	0.4
Par*Vcrim	Parent*VCrime	132.1	314.9
Par*Nstuds	Parent*NStudnts	3.0	6.3
Par*Stuexp	Parent*StudExp	1.2	2.6
Par*PupT	Parent*Pupteach	3.5	7.3
White*PNW	White*Pnonwhite	16.5	16.3
USCit*PFB	USCit*Pforborn	8.4	10.6
Ind*Pats	Industry*Pats	30.1	64.7
Pdoc*JanSun	Postdoc* JanSun	75.6	84.2
Pdoc *JulRH	Postdoc* JulyRH	28.0	30.8
Pdoc *SupFun	Postdoc* SupFund	4.0	9.1
Pdoc *ArtEnt	Postdoc* Art_Ent	18.2	21.0
Pdoc *Ctime	Postdoc* ComTime	12.4	13.4
Pdoc *PFB	Postdoc* Pforborn	6.5	9.9

Table 15

Coefficient Estimates from Hybrid Conditional Logit Models

	Sample: Ph.D.s without Contractual Obligation to Previous Employers (N= 18,795)								
	Choice Set Size = 6			Choice Set Size = 11			Choice Set Size = 26		
Variable	Model 1 (Draw 1)	Model 2 (Draw 2)	Model 3 (Draw 3)	Model 4 (Draw 1)	Model 5 (Draw 2)	Model 6 (Draw 3)	Model 7 (Draw 1)	Model 8 (Draw 2)	Model 9 (Draw 3)
CompCons	0.00005[B]	0.00004	0.00003	0.00004[A]	0.00005[B]	0.00006[B]	0.00007[C]	0.00008[C]	0.00008[C]
Distance	0.8025[C]	0.8680[C]	0.8979[C]	0.9686[C]	1.0559[C]	0.9834[C]	1.1780[C]	1.1425[C]	1.1759[C]
JanSun	-0.0014[C]	-0.0017[C]	-0.0013[C]	-0.0012[C]	-0.0015[C]	-0.0017[C]	-0.0018[C]	-0.0017[C]	-0.0018[C]
JanTemp	0.0072[C]	0.0067[C]	0.0075[C]	0.0080[C]	0.0093[C]	0.0076[C]	0.0093[C]	0.0092[C]	0.0087[C]
JulRH	-0.0042[C]	-0.0056[C]	-0.0041[C]	-0.0051[C]	-0.0058[C]	-0.0047[C]	-0.0073[C]	-0.0073[C]	-0.0073[C]
JulTemp	-0.0034	-0.0054	-0.0068	-0.0062	-0.0111[B]	-0.0051	-0.0139[C]	-0.0155[C]	-0.0132[C]
PWater	-0.0002	-0.0002	-0.0003	-0.0005	-0.0019[A]	-0.0020[B]	-0.0026[C]	-0.0025[C]	-0.0021[C]
Coast	0.0525	0.0743[A]	0.0582[B]	0.1093[C]	0.0910[C]	0.1161[C]	0.1444[C]	0.1468[C]	0.1395[C]
Vcrime	-0.00002	-0.00001	-0.00003	0.00005	0.00001	0.00004	0.00003	0.00004	0.00001
Parkacre	-0.0018	-0.0022[A]	-0.0017	-0.0003	-0.0017	-0.0013	-0.0016	-0.0019[A]	-0.0018[A]
BadAQ	-0.0035[C]	-0.0035[C]	-0.0031	-0.0016[C]	-0.0037[C]	-0.0033[C]	-0.0034[C]	-0.0032[C]	-0.0037[C]
Supfund	0.0011	0.0011	0.0017	0.0007	0.0020	0.0020	0.0027[B]	0.0034[C]	0.0031[C]
Art_Ent	-0.0004	0.0008	-0.0006	-0.0018	-0.0015	-0.0015	-0.0031[C]	-0.0026[B]	-0.0025[C]
Studexp	-0.0085	-0.0169	-0.0153	-0.0028	-0.0125	-0.0010	-0.0183	-0.0237	-0.0204
PupTeach	-0.0087[C]	-0.0081[B]	-0.0093[C]	-0.0069[B]	-0.0090[C]	-0.0065[B]	-0.0095[C]	-0.0086[C]	-0.0087[C]
NStudnts	-0.0025	-0.0032	-0.0063	-0.0081	-0.0032	-0.0035	-0.0073	-0.0034	-0.0042
Comtime	-0.0060	-0.0039	-0.0034	-0.0090[A]	-0.0076	-0.0088[A]	-0.0119[B]	-0.0110[B]	-0.0089[A]
MSASize	0.0111[B]	0.0112[B]	0.0078	0.0048	0.0119[C]	0.0070	0.0106[B]	0.0122[C]	0.0096[B]
PopDens	-0.0135	-0.0211	-0.0179	-0.0411[C]	-0.0116	-0.0248	-0.0380[C]	-0.0289[B]	-0.0416[C]
PerDem	0.0008	0.00001	0.0007	0.0015[B]	0.0001	0.0005	0.0009	0.0004	0.0006
PerBach	0.0022	0.0010	0.0012	0.0046[B]	0.0028	0.0026	0.0042[B]	0.0053[C]	0.0046[C]
Pnonwhite	0.0073[C]	0.0094[C]	0.0091[C]	0.0078[C]	0.0084[C]	0.0076[C]	0.0097[C]	0.0096[C]	0.0093[C]
Pforborn	0.0159[C]	0.0155[C]	0.0149[C]	0.0184[C]	0.0178[C]	0.0195[C]	0.0238[C]	0.0224[C]	0.0239[C]
HighEd	0.0015	0.0016	0.0018	0.0047[B]	0.0034[A]	0.0033[A]	0.0085[C]	0.0073[C]	0.0083[C]

Pats	0.0005[A]	0.0007[B]	0.0005[A]	0.0007[B]	0.0006[B]	0.0008[B]	0.0012[C]	0.0013[C]	0.0011[C]
NorthAtl	0.1165	0.1481[B]	0.1273[A]	0.1223[A]	0.1127[A]	0.1097	0.1102[A]	0.1242[A]	0.1195[A]
SouthAtl	0.1292[C]	0.1493[C]	0.1318[C]	0.0876[B]	0.1491[C]	0.1475[C]	0.1824[C]	0.1704[C]	0.1845[C]
NorthCen	0.0501	0.0515	0.0783	0.0342	0.0510	0.0619	0.0678	0.0605	0.0752[A]
Mount	0.2181[C]	0.1726[B]	0.2080[C]	0.1119[A]	0.1580[B]	0.2161[C]	0.0640	0.0314	0.0539
Pacific	0.4502[C]	0.4510[C]	0.4148[C]	0.4199[C]	0.3437[C]	0.4130[C]	0.2955[C]	0.2669[C]	0.3021[C]
Age*Dist	-0.0509[C]	-0.0533[C]	-0.0539[C]	-0.0575[C]	-0.0601[C]	-0.0575[C]	-0.0650[C]	-0.0635[C]	-0.0648[C]
Marr*Dist	-0.2847[C]	-0.2642[C]	-0.2835[C]	-0.3012[C]	-0.2988[C]	-0.3084[C]	-0.3135[C]	-0.3256[C]	-0.3146[C]
C_Ph.D.*Dist	-0.4272[C]	-0.4130[C]	-0.4283[C]	-0.4357[C]	-0.4332[C]	-0.4389[C]	-0.4880[C]	-0.4985[C]	-0.4900[C]
Par*VCrim	-0.0003[C]	-0.0003[C]	-0.0002[C]	-0.0003[C]	-0.0003[C]	-0.0002[C]	-0.0003[C]	-0.0002[C]	-0.0003[C]
Par*Nstuds	0.0092	0.0195[A]	0.0265[B]	0.0289[C]	0.0200[A]	0.0298[C]	0.0230[B]	0.0241[B]	0.0247[B]
Par*Stuexp	-0.0953[C]	-0.0674[C]	-0.0754[C]	-0.0681[C]	-0.0762[C]	-0.0731[C]	-0.0788[C]	-0.0786[C]	-0.0795[C]
Par*PupT	0.0006	-0.0013	0.0018	-0.0028	0.0007	-0.0029	0.0008	0.0005	0.0004
White*PNW	-0.0107[C]	-0.0111[C]	-0.0109[C]	-0.0113[C]	-0.0115[C]	-0.0109[C]	-0.0118[C]	-0.0115[C]	-0.0115[C]
USCit*PFB	-0.0113[C]	-0.0116[C]	-0.0120[C]	-0.0126[C]	-0.0123[C]	-0.0140[C]	-0.0140[C]	-0.0143[C]	-0.0143[C]
Ind*Pats	0.0005	0.0006[A]	0.0007[A]	0.0011[C]	0.0014[C]	0.0011[C]	0.0018[C]	0.0018[C]	0.0019[C]
Pdoc*JanSun	0.0010[A]	0.0010[B]	0.0010[B]	0.0015[C]	0.0012[B]	0.0014[C]	0.0020[C]	0.0020[C]	0.0021[C]
Pdoc*JulRH	0.0004	0.0011	-0.0002	0.0002	0.0001	0.0003	-0.0018	-0.0023[A]	-0.0019[C]
Pdoc*SupFun	-0.0003	-0.0009	-0.0013	-0.0007	-0.0009	-0.0012	-0.0022	-0.0026	-0.0023
Pdoc*ArtEnt	0.0019	0.0007	0.0014	0.0004	0.0029[B]	0.0029[B]	0.0057[C]	0.0057[C]	0.0050[C]
Pdoc*CTime	0.0128[B]	0.0079	0.0082	0.0108[B]	0.0104[B]	0.0125[B]	0.0177[C]	0.0151[C]	0.0151[C]
Pdoc*PFB	-0.0081[C]	-0.0061[B]	-0.0048	-0.0063[B]	-0.0086[C]	-0.0092[C]	-0.0134[C]	-0.0126[C]	-0.0122[C]
Log-Likeli	-28442	-28474	-28473	-38004	-38037	-38078	-50646	-50644	-50647
Pseudo R^2	0.155	0.154	0.154	0.157	0.156	0.155	0.173	0.173	0.173

[A] Indicates the coefficient is significantly different from zero at the 10% level of significance.
[B] Indicates the coefficient is significantly different from zero at the 5% level of significance.
[C] Indicates the coefficient is significantly different from zero at the 1% level of significance.

Table 16

Hausman-McFadden Tests for IIA
Conditional Logit Models

Model CL: New Employees (Table 12)	Chi-Sq Stat	Critical Chi-Sq Stat	Comment
1: CC=6, Draw 1	9.26	43.7	No Rejection*
2: CC=6, Draw 2	12.31	43.7	No Rejection
3: CC=6, Draw 3	12.11	43.7	No Rejection
1: CC=11, Draw 1	7.87	43.7	No Rejection
2: CC=11, Draw 2	4.94	43.7	No Rejection
3: CC=11, Draw 3	4.07	43.7	No Rejection
1: CC=26, Draw 1	0.74	43.7	No Rejection
2: CC=26, Draw 2	1.46	43.7	No Rejection
3: CC=26, Draw 3	0.59	43.7	No Rejection

*Indicates the Null Hypothesis of IIA cannot be rejected at the 95% level of significance.
(d.f. equals 30 in all tests)

Table 17

Coefficient Estimates from Mixed Logit Models

	Specification I: No Interaction Terms			Specification 2: With Interaction Terms		
	Choice Set Size = 26			Choice Set Size = 26		
Variable	Draw 1	Draw 2	Draw 3	Draw 1	Draw 2	Draw 3
CompCons	0.00015[C]	0.00016[C]	0.00016[C]	0.00009[C]	0.00009[C]	0.00009[C]
Distance	-1.1659[C]	-1.1665[C]	-1.1678[C]	1.1463[C]	1.1010[C]	1.1365[C]
JanSun	-0.00014	-0.00003	-0.00005	-0.0014[C]	-0.0012[C]	-0.0013[C]
Ns JanSun	0.00011	0.00001	0.00020	n/a	n/a	n/a
JanTemp	0.0021	0.0029	0.0022	0.0026	0.0029	0.0021
STD JanTemp	0.0145[C]	0.0132[C]	0.0133[C]	0.0151[C]	0.0145[C]	0.0152[C]
JulRH	-0.0089[C]	-0.0093[C]	-0.0092[C]	-0.0080[C]	-0.0081[C]	-0.0082[C]
JulTemp	-0.0134[C]	-0.0154[C]	-0.0129[C]	-0.0099[A]	-0.0123[B]	-0.0099[A]
PWater	-0.0017[A]	-0.0014	-0.0010	-0.0015	-0.0013	-0.0010
Coast	0.1825[C]	0.1873[C]	0.1773[C]	0.1823[C]	0.1863[C]	0.1800[C]
Vcrime	0.00001	0.00003	0.00001	0.0001	0.0001	0.0001
Parkacre	-0.0015	-0.0018[A]	-0.0016	-0.0013	-0.0017[A]	-0.0015
BadAQ	-0.0026[B]	-0.0025[B]	-0.0032[C]	-0.0027[C]	-0.0026[B]	-0.0031[C]
Supfund	0.0004	0.0010	0.0010	0.0013	0.0021[A]	0.0019
Art_Ent	-0.0028[C]	-0.0027[C]	-0.0030[C]	-0.0040[C]	-0.0037[C]	-0.0036[C]
Studexp	-0.0560[C]	-0.0590[C]	-0.0592[C]	-0.0356[A]	-0.0440[B]	-0.0462[B]
STD Studexp	0.2120[C]	0.2246[C]	0.2337[C]	0.1510[C]	0.1734[C]	0.1923[C]
PupTeach	-0.0126[C]	-0.0119[C]	-0.0118[C]	-0.0123[C]	-0.0112[C]	-0.0108[C]
NStudnts	-0.0142[C]	-0.0105[B]	-0.0117[B]	-0.0148[C]	-0.0115[B]	-0.0131[B]
Comtime	-0.0017	-0.0025	-0.0005	-0.0057	-0.0049	-0.0031
MSASize	0.0094[B]	0.0116[C]	0.0087[B]	0.0087[B]	0.0109[B]	0.0078[A]
PopDens	-0.0629[C]	-0.0601[C]	-0.0744[C]	-0.0679[C]	-0.0607[C]	-0.0755[C]
PerDem	0.0013[B]	0.0008	0.0010	0.0009	0.0004	0.0007
PerBach	0.0071	0.0081	0.0071	0.0072[C]	0.0080[C]	0.0070[C]
Pnonwhite	0.0014[C]	0.0015[C]	0.0013[C]	0.0091[C]	0.0090[C]	0.0089[C]
STD Pnonwhite	0.0193[C]	0.0241[C]	0.0251[C]	0.0063	0.0143	0.0158[B]
Pforborn	0.0078[C]	0.0067[C]	0.0082[C]	0.0222[C]	0.0208[C]	0.0222[C]
HighEd	0.0104[C]	0.0096[C]	0.0106[C]	0.0088[C]	0.0078[C]	0.0090[C]
Pats	0.0002	0.0004	0.0004	-0.0001	0.0001	0.0001
STD Pats	0.0066[C]	0.0065[C]	0.0062[C]	0.0048[C]	0.0046[C]	0.0043[C]
NorthAtl	0.0368	0.0498	0.0524	0.1125[A]	0.1275[A]	0.1295[B]
SouthAtl	0.1548[C]	0.1555[C]	0.1763[C]	0.1631[C]	0.1571[C]	0.1779[C]
NorthCen	-0.0087	-0.0010	0.0175	0.0207	0.0214	0.0385
Mount	-0.0384	-0.0720	-0.0521	-0.0084	-0.0482	-0.0311
Pacific	0.4175[C]	0.3820[C]	0.4301[C]	0.4071[C]	0.3714[C]	0.4141[C]
Age*Dist	n/a	n/a	n/a	-0.0657[C]	-0.0640[C]	-0.0655[C]
Marr*Dist	n/a	n/a	n/a	-0.3306[C]	-0.3447[C]	-0.3322[C]
C_Ph.D.*Dist	n/a	n/a	n/a	-0.5002[C]	-0.5122[C]	-0.4978[C]
Par*VCrim	n/a	n/a	n/a	-0.0003[C]	-0.0003[C]	-0.0003[C]

Par*Nstuds	n/a	n/a	n/a	0.0227[B]	0.0238[B]	0.0239[B]
Par*Stuexp	n/a	n/a	n/a	-0.0819[C]	-0.0811[C]	-0.0840[C]
Ns Par*Stuexp	n/a	n/a	n/a	0.0184	0.0172	0.0176
Par*PupTeach	n/a	n/a	n/a	0.0020	0.0016	0.0017
White*PNW	n/a	n/a	n/a	-0.0126[C]	-0.0121[C]	-0.0122[C]
STD White*PNW	n/a	n/a	n/a	0.0181[C]	0.0144[B]	0.0127
USCit*PFB	n/a	n/a	n/a	-0.0139[C]	-0.0144[C]	-0.0143[C]
Ind*Pats	n/a	n/a	n/a	0.0011[B]	0.0012[B]	0.0012[B]
STD Ind*Pats	n/a	n/a	n/a	0.0050[C]	0.0049[C]	0.0049[C]
Pdoc*JanSun	n/a	n/a	n/a	0.0022[C]	0.0021[C]	0.0023[C]
Pdoc*JulRH	n/a	n/a	n/a	-0.0011	-0.0016	-0.0011
Pdoc*SupFun	n/a	n/a	n/a	-0.0019	-0.0022	-0.0020
Pdoc*ArtEnt	n/a	n/a	n/a	0.0051[C]	0.0051[C]	0.0044[C]
Pdoc*CTime	n/a	n/a	n/a	0.0164[C]	0.0134[C]	0.0134[C]
Pdoc*PFB	n/a	n/a	n/a	-0.0124[C]	-0.0114[C]	-0.0110[C]
Log-Likelihood	-51207	-51200	-51207	-50588	-50589	-50593
Pseudo R^2	0.164	0.164	0.164	0.174	0.174	0.174

[A] Indicates the coefficient is significantly different from zero at the 10% level of significance.
[B] Indicates the coefficient is significantly different from zero at the 5% level of significance.
[C] Indicates the coefficient is significantly different from zero at the 1% level of significance.

CHAPTER 6

WILLINGNESS TO PAY ESTIMATES

The results presented in Chapter 5 offer insight into Ph.D.s' qualitative preferences toward MSA attributes. However, the estimated utility coefficients can provide only limited insight into preference intensities, or the extent to which the attributes of MSAs affect Ph.D.s' location choice. To gain a more comprehensive understanding of the role of amenities in location choice, this chapter translates the utility coefficients estimated in Chapter 5 into willingness to pay (WTP) estimates. Estimating willingness to pay is analogous to asking, "If the level of an attribute increased by 10% percent in all MSAs, how much private consumption could we take away from (or give to) each Ph.D. such that their expected utility level remain unchanged?" In answering this question, the WTP estimates facilitate an equalized measure of the relative importance of attributes on Ph.D. location choice. [94]

To assess the reliability of the estimates across models, WTP is calculated using coefficients from four different types of random utility models: the simple conditional logit, the simple mixed logit, the hybrid conditional logit, and the hybrid mixed logit model.[95] The remainder of this chapter is organized as follows. Section A presents the WTP estimates using the estimated coefficients from the simple specifications of the

[94] All WTP estimates are reported in constant 1999 dollars.
[95] The marginal WTP estimates, or the implicit prices attributes, are reported in Table A8 of the appendix. The implicit price represents the amount a Ph.D. pays for unit change in the value of an attribute

conditional and mixed logit models (e.g.,, the models that do not control for observed preference heterogeneity). These estimates provide insight into the relative values for attributes across the full population of Ph.D.s in our sample. Section B reports the WTP estimates using the coefficients from the conditional and mixed logit hybrid models, and provides greater insight into how values for attributes vary across observable characteristics of Ph.D.s. Section C summarizes the main findings of this chapter.

A. Simple Specifications

Each WTP estimate represents the average amount a Ph.D.'s net income must change after a 10% increase to the value of the attribute in order to keep their utility constant. The WTP estimates are calculated for each attribute as follows. First, each Ph.D.'s expected maximum utility is estimated before any changes are made to the level of amenities in cities. This is calculated as the product of the utility coefficients from the RUM, and the observed levels of each attribute in all cities, or:

$$EU^{BASE} = ln \sum_{j=1}^{J} \{\exp(\hat{B}_1 X_{1j} + \hat{B}_2 X_{2j} + ... + \hat{B}_n X_{nj})\} \tag{40}$$

where $\hat{B}_1$ represents the estimated coefficient on attribute X_1, $\hat{B}_n$ represents the estimated coefficient on attribute X_n, and EU^{BASE} represents Ph.D.s' baseline expected maximum utility level. Next, the level of the attribute in question, X_1, is exogenously increased by 10% in all cities, and the new maximum expected utility level, EU^{NEW}, is computed with the change in the attribute set:

$$EU^{NEW} = ln \sum_{j=1}^{J} \{\exp(\hat{B}_1 X_{1j}^{*} + \hat{B}_2 X_{2j} + ... + \hat{B}_n X_{nj})\} \tag{41}$$

where the vector X_{1j}^{*} denotes that city *j* has a 10% greater amount of attribute X_1 than previously. Finally, each Ph.D.'s WTP for a 10% increase in attribute X_1 equals the change in expected utility divided by the coefficient on private consumption, or:

$$\text{WTP}=(EU^{NEW} - EU^{BASE})/\ \hat{\psi} \tag{42}$$

where $\hat{\psi}$ is the coefficient on private consumption that converts the utility difference into monetary terms.

Intuitively, a WTP estimate for attribute *X* of say, $1,000, indicates that on average Ph.D.s are willing to sacrifice $1,000 of private consumption for a 10% increase in the level of attribute *X* in all MSAs. Similarly, a WTP estimate of -$1,000 suggests that on average Ph.D.s are willing to pay $1,000 for a 10% decrease in the level of amenity *X* in all MSAs.

Table 18 reports the WTP estimates for city attributes using the coefficient estimates from the simple specifications of the conditional and mixed logit models. For simplicity, the WTP estimates reported in Table 18 are calculated using the coefficients from the same choice set sample; draw 3 of choice set 26. The WTP estimates are separately calculated for all city attributes, excluding the control variables, MSA size, population density, and the region indicators. Model 1 (column 3) reports the WTP estimates for the simple specification of the conditional logit model, and Model 2 (column 4) reports the WTP estimates for the simple specification of the mixed logit model. Table 18 also reports the mean value of a 10% change for each attribute and an indicator for whether the estimated coefficient from the model was significant at the 10% level or better.[96]

The WTP estimates give us a sense of the relative values Ph.D.s place on amenities, and therefore provide some indication as to the impact amenity changes have on Ph.D. location choice. With this in mind, it is evident from Table 18 that Ph.D.'s place substantially larger values toward natural amenities than other city attributes. The highest valued attribute, due to its binary nature, is the value of living on the coastline. The estimates from the conditional (CL) and mixed logit (MXL) models, respectively, suggest that Ph.D.s are willing to pay $8,156 and $11,856 to live on the coastline. Of the continuous variables, Ph.D.s reveal the strongest preferences for summer temperatures and summer humidity (*JulyRH*). The results from both the CL and MXL models suggest that Ph.D.s are willing to pay more than $6,000 to avoid a 10% increase in *JulyTemp*, and approximately $3,000 to avoid a 10% increase in *JulyRH*.[97] The results also suggest that changes in winter temperatures can have a substantial effect to Ph.D. welfare. The estimates from the CL model imply that Ph.D.s are willing to pay $1,856 for a 10% increase in January temperatures.[98]

The WTP estimates on publicly-provided amenities are generally much lower in absolute value. One exception is the surprisingly large and counterintuitive estimated value for expenditures per student. The MXL model suggests that Ph.D.s value a 10%

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[96] Note the indicator for significance does not indicate that the willingness to pay estimate is significantly different from zero, but that the estimated coefficient on the variable was significant at the 10% level or better in the RUM.

[97] The interpretation of a 10% increase in variables that are already defined in percentage terms can be confusing. The change represents a percentage increase relative to the current levels, not a percentage increase in absolute terms. For example, a 10% increase in July relative humidity in a city would be represented by a change from 60% to 66%, not a change from 60% to 70%.

[98] To place the estimates in perspective, the mean estimated net income for all Ph.D.s equals $33,309. Thus, the estimates suggest that, on average, Ph.D.s are willing to sacrifice approximately 5.5% of their net income for a 10% increase in January temperatures.

decrease in expenditures per student at over $2,000; the estimate from the CL model is approximately $940. These large estimates suggest that the variable is likely capturing more than just the influence of spending on students. For instance, Berne and Steifel (1994) found a positive relationship between poverty rates, as measured by the percent of students who qualified for the free lunch program, and per pupil spending. Thus, the large negative estimate on *Studexp* may reflect a broader distaste for MSAs with higher property tax rates and/or higher poverty rates.

The WTP estimates are lower in absolute value for the remaining publicly-provided amenities. The results from both models suggest that Ph.D.s value a 10% improvement in air quality at approximately $200. Congestion may have a greater impact on Ph.D. welfare than air quality. The estimates from the CL model suggest that new Ph.D.s are willing to pay $940 for a 10% decrease in commute times. The value of pupil to teacher ratios is within a similar range. The estimates from the CL and MXL models suggest that Ph.D.s value a 10% decrease in pupil to teacher ratios at $1,018 and $1,273, respectively.

The WTP estimates for changes in the demographic composition of MSAs are similar in magnitude to those of the publicly-provided amenities. The estimates for a 10% increase in the percent highly educated range from $591in the CL model to $1,088 in the MXL model. In addition, the estimated value placed on a 10% increase in the percent foreign born is approximately $500 and $400 in the CL and MXL models, respectively, while the same increase in percent non-white is valued at $366 in the CL model. Finally, the CL models suggest Ph.D.s are willing to pay $462 and $257 for a

10% increase in the number of patents and the number of universities in an MSA, respectively.

B. Hybrid Specifications

Table 19 presents the WTP estimates based on the hybrid specifications of the conditional and mixed logit models. The estimates are calculated using the coefficients from the same choice set samples as earlier (choice set size 26, draw 3). The method of estimating WTP for the hybrid specifications is the same as described in the previous section, except relevant individual characteristics are included in the formulation of expected utility (see Table 14 for the list of relevant individual characteristics).

The inclusion of the interaction terms allows us to estimate how values vary across groups of Ph.D.s. For instance, the inclusion of the interacted term *V*cr*ime*Parent* allows us to assess the welfare changes associated with a 10% in violent crime for both parents and Ph.D.s without children. To facilitate comparison across observable characteristics, Table 19 reports the WTP estimates on interacted variables for both relevant groups. Non-interacted variables, on the other hand, do not systematically vary across observable characteristics of Ph.D.s. Thus, Table 19 reports only one estimate for non-interacted variables, reflecting the average willingness to pay across the entire sample of Ph.D.s.

The estimates from the hybrid models are qualitatively similar to the non-hybrid models, but generally larger in magnitude. For example, the hybrid specifications of the CL and MXL models suggest that Ph.D.s value the coast at $19,253 and $18,326, respectively. These estimates are more than $8,000 greater than the comparable estimates from the simple specifications. The primary reason the estimates are higher in magnitude in the hybrid specifications is the difference in the estimated coefficient on private consumption. Recall, the coefficient on private consumption represents Ph.D.s' marginal utility of income, and the WTP estimates are very sensitive to its value. A lower marginal utility of income, other things constant, implies larger willingness to pay estimates (see equation 42). The coefficients on private consumption are approximately 50% smaller in the hybrid models than in the simple specifications, implying that attribute values are approximately twice as large in absolute terms, other things equal.

Despite the quantitative differences, the attributes' relative values are very similar across specifications. As in the non-hybrid models, the climate variables are shown to be the highest valued attributes among Ph.D.s. The results from the CL and MXL models, respectively, suggest that Ph.D.s are willing to pay approximately \$13,000 and \$8,000 for a 10% increase in July temperature. In addition, the estimates for July humidity range between \$5,000 and \$6,857 in the CL and MXL models, respectively. January temperatures are also highly valued. The results from the CL hybrid model suggest that Ph.D.s are willing to pay \$4,222 for a 10% increase in January temperature. In comparison, the estimates from the CL and MXL models suggest Ph.D.s are willing to pay \$436 and \$297 for a 10% improvement in air quality, respectively.

The strength of the hybrid models is their ability to inform policymakers as to how changes to amenity levels may impact different subgroups of the population of Ph.D.s. To facilitate comparison across observed characteristics, Table 19 categorizes the WTP estimates by individual characteristics for interacted variables. The estimates from the CL model suggest that parents are willing to pay \$1,817 for a 10% reduction in violent crime rates, while the comparable willingness to pay for Ph.D.s without children is virtually zero ($90 but not statistically significant). The implication is that lowering violent crime rates in a city can be an important draw for Ph.D.s with children, but would likely have a small impact on the location choices of Ph.D.s without children.

The values Ph.D.s place on certain amenities vary substantially across sector choice. For instance, the estimates from the CL model suggests that Ph.D.s in industry value are willing to pay $1,445 for a 10% increase in the number of patents in cities, compared to only $474 for faculty and postdocs. In addition, the WTP estimates on hours of January sunlight, the number of art and entertainment enterprises, and commute times are all positive for postdocs, but negative for industrial Ph.D.s and faculty.[99] The difference in the values across sectors exceeds $3,000 for four of the seven attributes.

The diversity variables also take on considerably different values across socio-demographic groups. For instance, the CL model suggests that nonwhites value a 10% increase in the percentage of nonwhite residents at $2,713, whereas whites are willing to pay $719 for a 10% decrease in the percentage of nonwhite residents. Similarly, the results suggest foreign-born Ph.D.s are willing to pay approximately $300 more for a 10% increase in the percentage of foreign-born residents than are U.S. citizens. These results are enlightening in light of Florida's (2002a, 2002b) works, which have asserted the importance of diversity to the highly educated. The estimates do not run counter to the idea that the highly educated prefer diversity; in fact, the results suggest that, on average, new Ph.D.s are more likely to choose cities with more diversity, other things equal. However, the results imply that this outcome is largely driven by the location choices of nonwhite and foreign-born Ph.D.s.

[99] The negative estimate on January sunlight is likely driven by the "Pacific-Northwest effect" discussed in Chapter 5, which was particularly strong for Ph.D.s in industry

Due to the unique nature of the model used to arrive at these estimates, many of the estimates presented here are not directly comparable to the estimates found in previous studies. One notable exception is Cragg and Kahn (1997), who estimate demand for several climate attributes using a random utility model on individual state location choices. Table A.10 in the appendix provides a summary of how our findings on selected climate variables compare to those reported in Cragg and Kahn's paper. The results are generally within a favorable range of one another. Notably, the authors estimate that college graduates are willing to pay between $984 and $5,788 for a 5.2 degree decrease in July temperatures, where as our estimates range between $6,068 and $6,495 for an average decrease of 7.4 degrees. In addition, the authors estimated values for July relative humidity range between $846 and $3,906; our comparable estimates range from $2,990 to $3,246. Finally, Cragg and Kahn find demand estimates for winter (February) temperatures ranging from $1,182 to $10,860, while we find willingness to pay estimates that range between $497 and $1,856.[100]

In assessing the accuracy of these estimates, one must consider a number of factors relating to how closely the model can approximate the actual job/city choice process faced by Ph.D.s at the time of degree. All random utility models must assume that an individual has complete information regarding the set of attributes available in each alternative prior to making the choice, and that they are able to recognize the trade-offs among attributes in each alternative (McFadden, 2004). While the validity of this

[100] The estimates on winter temperatures reported here appear to be substantially different from the estimates found by Cragg and Kahn. However, the variation is largely attributable to the difference in the amount that temperature changes. In particular, in Cragg and Kahn's paper the estimates reflect the willingness to pay for a 10.4 degree increase in February temperature, whereas our estimates reflect the willingness to pay for an average increase of only 3.7 degrees in January temperature.

assumption is questionable in all discrete choice models, we recognize that it is particularly dubious in this application.

The choice of where to work and live is very complex and heterogeneous, and new Ph.D.s, most of whom are inexperienced in making employment related decisions, may not be fully aware of precisely what their choice entails. For example, a new Ph.D. who has never seen an income above, say, $20,000, may overestimate the potential consumption power of $60,000 simply because they cannot draw upon previous experiences to process and appreciate the real value of that income.[101] Consequently, new Ph.D.s' ability to relate their expected income with the amenity levels in alternatives may be somewhat clouded. This is not to say that a new Ph.D.'s choice of city will not be based on (and reveal) their preferences for city attributes; rather, that the imputed values for amenities, or willingness to tradeoff income, may be biased due to the cognitive context surrounding this choice.

C. Summary

This chapter has provided insights into the relative importance of MSA attributes on Ph.D. location choice by estimating Ph.D.s willingness to pay for equal percentage changes in the level of amenities. In both the simple and hybrid specifications, the estimates are substantially higher for climate variables than for publicly-provided amenities or other attributes. Specifically, the highest valued attributes of all continuous variables are those indicating general climate (*JulyTemp*, *JulyRH*, and *JanTemp*). Of publicly-provided amenities that are significant and of the expected sign, the highest

[101] This is more of an issue with industrial Ph.D.s and faculty than for postdocs, simply because postdocs will not realize as drastic a change an income in their new position.

valued attribute is pupil to teacher ratios in public schools (*Pupteach*), followed by commute time to work (*ComTime*) and the level of air quality in the MSA (*BadAQ*).

In addition, it is evident from these results that the magnitudes of the WTP estimates are dependent on the structure of the model. The models that control for observable heterogeneity have significantly larger WTP estimates. These quantitative differences are largely driven by the lower estimated marginal utility of income in the hybrid specifications. However, the relative values of amenities are generally consistent across specifications.

The hybrid specifications also highlight differences in valuations across observable characteristics of Ph.D.s. In particular, the results suggest that nonwhite Ph.D.s have a higher preference for cities with a higher level of racial diversity, and parents are more concerned with the level of violent crime in a city than are Ph.D.s without children. The estimates also illustrate that sector choice plays a large role in how Ph.D.'s value amenities. Based on these results, we now consider potential policy implications of results, acknowledge the limitations of the analysis, and discuss potential avenues for future research.

Table 18

Mean Willingness to Pay for 10% Changes in Attribute Values:
Simple Specification

Variable	Mean 10 % change	Model (1): [A] Cond'l Logit (Spec 1)	Model (2): [B] Mixed Logit (Spec 1)
Coast[1]	n/a	8,156*	11,696*
JanSun	15.2	-726*	-48
JanTemp	3.7	1,856*	497
JulRH	5.7	-2,990*	-3,246*
JulTemp	7.6	-6,495*	-6,068*
PWater	0.83	-131*	-50*
Vcrime	56.2	-179	18
Parkacre	435	-38*	-34*
BadAQ	0.82	-202*	-173*
Supfund	0.31	46*	22
Art_Ent	3.6	-174*	-667*
Studexp	599	-943*	-2,231*
PupTeach	1.7	-1,018*	-1,273*
NStudnts	1.7	-140*	-1,236
Comtime	2.3	-940*	-73
PerDem	4.6	322	298
PerBach	2.4	591*	1,088*
Pnonwhite	2.0	366*	197
Pforborn	0.74	508*	401*
HighEd	0.34	257*	281*
Pats	2.8	462*	74

[A] Estimates are based upon the coefficients in Model 9 of simple conditional logit (Table 15).
[B] Estimates are based upon the coefficients in Model 3 of simple mixed logit (Table 17).
[*] Indicates that the estimated coefficient on the attribute was significant at the 10% level or better.
[1] Represents a change from 0 to 1

Table 19

Mean Willingness to Pay for 10% Changes in Attribute Levels:
Hybrid Models

Non-Interacted Variables	Mean 10% change	Model (3): [A] Conditional Logit Hybrid		Model (4): [B] Mixed Logit Hybrid	
Coast[1]	n/a	18,326*		19,253*	
JanTemp	3.7	4,222*		792	
JulTemp	7.6	-13,049*		-7,975*	
PWater	0.83	-236*		-88	
Parkacre	435	-78		-57	
BadAQ	0.82	-436*		-297*	
PerDem	4.6	360		328	
PerBach	2.4	1,522*		1,829*	
HighEd	0.34	491*		396*	
		Group 1	Group 2	Group 1	Group 2
Interacted Variables	Mean 10% change	Postdoc=0	Postdoc=1	Postdoc=0	Postdoc=1
JanSun	15.2	-3,589*	575*	-2,164*	1,556*
JulRH	5.7	-5,505*	-6857	-5,000*	-5,666
Supfund	0.31	153*	39*	75	-3
Art_Ent	3.6	-1,165*	1202*	-1,382*	286*
Comtime	2.3	-2,707*	1916*	-759*	2,583*
Pforborn	0.74	1,774*	2120*	1,249*	1,534*
		Parent=0	Parent=1	Parent=0	Parent=1
Vcrime	56.2	90	-1817*	371	-1287*
Studexp	599	-1,641*	-7880*	-3,018*	-8,335*
PupTeach	1.7	-1,997*	-1894	-2,002*	-1678
NStudnts	1.7	-925	4566*	-2,333*	1,943*
		White=0	White=1	White=0	White=1
Pnonwhite	2.0	2,713*	-575*	2,074*	-719
		US Cit=0	US Cit=1	US Cit=0	US Cit=1
Pforborn	0.74	2,156*	1,802*	1,598*	1,250*
		Industry=0	Industry=1	Industry=0	Industry=1
Pats	2.8	474*	1,445*	24	479*

[A] Estimates are based upon the coefficients in Model 9 of hybrid conditional logit (Table 16).
[B] Estimates are based upon the coefficients in Model 3 of hybrid mixed logit (Table 18).
[*] Indicates that the estimated coefficient on the attribute was significant at the 10% level or better.
[1] Represents a change from 0 to 1.

CHAPTER 7

CONCLUSION

Due to their role in enhancing regional productivity, Ph.D.s in science and engineering represent a very attractive cohort of the labor force to municipal policymakers. The flow of new Ph.D.s from graduate school to the labor force represents one means by which networks are created and knowledge is transferred. When hired by private firms new Ph.D.s not only transfer knowledge, but contribute to productivity by engaging in scientific discovery and improving technological innovation (Stern, 2004). New Ph.D.s in the academic sector also contribute to productivity through their scientific research and by training future productive workers. Despite the significant role these workers can play in innovation and economic development, to date relatively little is known regarding the factors that determine their location choices. This dissertation addresses this deficiency by using a random utility model framework to examine the role of amenities on the MSA location decisions of new S&E Ph.D.s.

The random utility models presented in this research represent the first models to estimate amenity values using individual location decisions at a city level and on a national scale. The primary advantage of using location decisions at the city/national level is that we can arrive at values for local public goods, such as air quality and crime, as well as for pure public goods, such as climate, in one framework. By focusing the analysis on the location decisions of new Ph.D.s in science and engineering, the results of this research help inform policymakers as to their ability (or inability) to attract and retain highly educated workers to their region through public investment in amenity quality.

The results provide several interesting insights into the influence of city attributes on the location choices of new Ph.D.s. The estimates of amenity values are generally higher in magnitude for natural amenities, such as summer and winter temperatures, than for publicly-provided amenities, such crime or air quality. The implication is that cities with superior natural amenities hold an advantage over other cities in terms of their ability to improve the composition their workforce. It is important to acknowledge, however, that the estimates may under-represent the true influence of some reproducible amenities because of the underlying assumption that the levels of amenities are constant within MSAs. An MSA has high crime areas and low crime areas, neighborhoods with good school districts and bad school districts, etc., that coexist within its borders. In reality, individuals may be more concerned with (and influenced by) the quality of these amenities within their neighborhood than with the average quality across their MSA. We assume that it is the average measure of these amenities across the MSA that influences their location decisions, not a neighborhood specific measure.

Future research could potentially address this issue by modeling residential location choices at a more spatially disaggregated level, such as the census tract level. After identifying individual location decisions and collecting the relevant data on amenities (e.g. crime rates, student expenditures, etc.) at the census tract level, one could develop a nested logit model in which an individual's MSA choice represents the upper nest, and an individual’s choice of census tract represents the lower nest. In this framework, MSA choice could be used to estimate values for amenities that are relatively constant in an MSA (climate), and the choice of census tract within an MSA could be used to estimate values for amenities that vary within MSAs (school quality, crime, proximity to superfund sites, etc.).

The results from this research do not, however, imply that reproducible amenities have no influence on the location choices of new S&E Ph.D.s. The models consistently suggest that new Ph.D.s are more likely to locate in cities with higher air quality, lower pupil to teacher ratios, less traffic, lower crime rates, and greater levels of diversity. Thus, abstracting from the costs of providing these amenities, the results suggest that improving the quality of these amenities will attract more highly skilled S&E workers to an area. Taken together, the effects could be substantial.

The analysis also illustrates how preferences vary across the population of Ph.D.s. Specifically, we compare models that control for observed heterogeneity (hybrid models) and unobserved heterogeneity (mixed logit models) with models that assume homogeneous preferences (simple conditional logit models). As a whole, the models that control for either unobserved or observed heterogeneity in preferences perform better than the models that do not control for either of these types of heterogeneity. This result is generally consistent with the findings of other studies that examine the impact of heterogeneous modeling techniques (Morey & Rossmann, 2003; Parsons & Massey, 2003). Furthermore, the coefficients on the interacted terms are generally consistent with economic intuition. Notably, the results consistently suggest that younger, single Ph.D.s are likely to move greater distances than older, married Ph.D.s; non-citizens are more likely to locate in cities with greater amounts of foreign born residents; white Ph.D.s are less drawn to cities with more racial diversity; and parents are less likely to locate in cities with higher violent crime rates. In addition, preferences for city attributes vary substantially depending on the Ph.D.'s choice of employment sector.

Prior to using the results of this analysis to guide public policy, a number of empirical issues need to be addressed. The analysis currently focuses on how amenities influence the location choices of new Ph.D.s. Absent from this model are characteristics which relate to the work and research environment of the doctoral science and engineering labor force. In particular, new Ph.D.s desire to work in an area that may facilitate better research opportunities, in which it is easier to obtain tacit knowledge, build networks and collaborate with other scientists. Areas richer in attributes relating to the work environment of new S&E Ph.D.s are more desirable not only because they may enhance one's own productivity and future employment prospects, but also because of the psychological gains associated with being around like-minded people. Variables that could account for these effects include measures of industrial and/or academic research and development expenditures, the composition of the workforce, as well as the number of top-ranked research institutions in the MSA.

There are a number of important empirical questions that remain unanswered by this study and are open to further investigation. In particular, this study provides insight into one of the potential streams of benefits policymakers can receive from improving amenities: the growth of a talented labor force. This study does not inform policymakers, however, whether it is worth investing in these amenities. Future research should address the efficiency of amenity improvement policies by weighing the potential long-term benefits associated with amenity changes against the costs of improving amenities.

In addition to examining the cost effectiveness of any amenity improvement investment policy, policymakers and researchers should also consider the effectiveness of alternative policies which can attract highly educated workers and stimulate economic growth. Investing in amenities is just one of a number of alternatives policymakers can act on in order to facilitate an increase in the proportion of highly educated in a particular region. Others include tax breaks to companies that employ highly educated workers, investment in higher education or workforce development facilities, or providing direct or indirect compensation to workers who locate in an area.

The discrete choice approach used in this dissertation is not the only empirical technique researchers used to estimate amenity values. Future research could compare the estimates found using a discrete choice model with those obtained from the traditional approach to estimating amenity demand, the hedonic model. The hedonic method assumes that in spatial equilibrium, the values of local public goods are fully capitalized into the wages and rents in each location. Amenity values can be found by specifying the amenity bundles across locations as a function of the spatial variation in housing prices and wages. This type of analysis is particularly feasible because we have already gathered the necessary data required to estimate hedonic equations; specifically, housing prices, wages, and amenity quality. The results would provide insight into the issues of comparability across estimation techniques, as well as provide confirmation as to the consistency and plausibility of the results from a particular method. The hedonic and discrete choice approaches could also be used to estimate the quality of life in MSAs and construct an ordinal ranking as to the attractiveness of cities to the highly educated scientific workforce.

Finally, it is important to recognize that the conclusions drawn from this study are limited in a number of ways. First, the analysis only includes new S&E Ph.D.s who had made a definite commitment to an employer at the time the survey was administered and reported an identifiable U.S. location. To the extent that this sample is not representative of the entire population of new S&E Ph.D.s, the inferences drawn regarding their preferences do not accurately represent the preferences of all new S&E Ph.D.s. Furthermore, previous studies which examine the economic benefits of a highly educated workforce relate these benefits to the stock of highly educated workers in an area. Due to the high turnover rate in the initial years of employment for new Ph.D.s, particularly postdocs, the ability of an area to improve its stock of highly educated workers would be better represented by the location choices of "seasoned" Ph.D.s, or those who have been employed for at least five years. The results are also limited due to the time period of the analysis. Specifically, the information-technology (IT) boom and strong labor market conditions in the late 1990s may be responsible for inflating or deflating some of the estimated amenity demand values. Whether and how the estimated values Ph.D.s' place on amenities changed following the IT boom could be investigated by extending the time period of the analysis to include post-2000 location choices.

APPENDIX A

Supplement to Chapter 3

Table A.1

Number and Percent of New S&E Ph.D.s in Each Sector with Definite Plans by Field
Graduating Years FY 1997-1999

Field	All S&E	Number Industry	Percent Industry	Number Academe	Percent Academe	Number Postdocs	Percent Postdocs	Number Other	Percent Other
Aerospace Engineering	435	176	40.5%	23	5.3%	101	23.2%	135	31.0%
Chemical Engineering	1348	838	62.2%	97	7.2%	314	23.3%	99	7.3%
Civil Engineering	1053	365	34.7%	218	20.7%	246	23.4%	224	21.3%
Electrical Engineering	3053	2019	66.1%	346	11.3%	322	10.5%	366	12.0%
Mechanical Engineering	1600	825	51.6%	196	12.3%	376	23.5%	203	12.7%
Other Engineering	3189	1431	44.9%	453	14.2%	821	25.7%	484	15.2%
Agriculture	1975	336	17.0%	466	23.6%	760	38.5%	413	20.9%
Astronomy	408	44	10.8%	30	7.4%	305	74.8%	29	7.1%
Biology	11051	647	5.9%	979	8.9%	8488	76.8%	937	8.5%
Chemistry	4289	1269	29.6%	369	8.6%	2437	56.8%	214	5.0%
Computer Science	1778	801	45.1%	539	30.3%	227	12.8%	211	11.9%
Earth Science	1292	268	20.7%	200	15.5%	626	48.5%	198	15.3%
Math	2340	496	21.2%	889	38.0%	703	30.0%	252	10.8%
Medicine	5290	463	8.8%	1491	28.2%	1776	33.6%	1560	29.5%
Physics	2569	688	26.8%	204	7.9%	1449	56.4%	228	8.9%
SUM	*41670*	*10666*	*25.6%*	*6500*	*15.6%*	*18951*	*45.5%*	*5553*	*13.3%*

Table A.2:

Descriptive Statistics by Type of Ph.D.

Variable Name	Variable Definition	New Ph.D.s with Definite Plans (N=41,670) Mean	New Ph.D.s without Definite Plans (N=23,757) Mean	*Difference*		New Ph.D.s with a known U.S. academic institution (N=15,809) Mean	New Ph.D.s with an unknown U.S. academic institution (N=6,896) Mean	*Difference*
age	Age of the individual at the time of Ph.D.	33.12	34.0	*-0.804*		33.05	32.50	*0.557*
male	Dummy variable indicating whether or not an individual is male	0.679	0.622	*0.057*		0.638	0.613	*0.025*
White	Dummy variable indicating whether or not an individual is White	0.651	0.577	*0.073*		0.679	0.657	*0.022*
Asian	Dummy variable indicating whether or not an individual is Asian or pacific islander	0.273	0.326	*-0.053*		0.246	0.256	*-0.010*
married	Dummy variable indicating whether or not an individual is married	0.583	0.563	*0.020*		0.566	0.539	*0.028*
child	Dummy variable indicating whether or not an individual is married with at least one child	0.255	0.227	*0.028*		0.234	0.205	*0.028*
UScit	Dummy variable indicating whether or not an individual is a U.S. citizen	0.670	0.614	*0.056*		0.676	0.690	*-0.014*
permres	Dummy variable indicating whether or not an individual is a permanent resident in the U.S.	0.080	0.108	*-0.028*		0.067	0.082	*-0.014*
tempres	Dummy variable indicating whether or not an individual is a temporary resident in the U.S.	0.241	0.259	*-0.018*		0.248	0.221	*0.027*
supp_Fellow	Dummy variable indicating whether or not individual's primary source of support during graduate school was fellowship or dissertation grant	0.165	0.138	*0.027*		0.180	0.191	*-0.011*
supp_TA	Dummy variable indicating whether or not individual's primary source of support during graduate school was teaching assistantship	0.143	0.165	*-0.022*		0.170	0.122	*0.048*
supp_RA_Tr	Dummy variable indicating whether or not individual's primary source of support during graduate school was research assistantship, internship, or traineeship	0.444	0.399	*0.045*		0.451	0.470	*-0.019*
supp_Emp	Dummy variable indicating whether or not individual's primary source	0.033	0.010	*0.024*		0.014	0.008	*0.006*

	of support during graduate school was employer reimbursement.						
preftemp	Dummy variable indicating whether or not an individual was full-time employed one year prior to Ph.D.	0.265	0.125	*0.140*	0.205	0.170	*0.035*
preptemp	Dummy variable indicating whether or not an individual was part-time employed one year prior to Ph.D.	0.063	0.111	*-0.047*	0.059	0.059	*0.000*
prefellow	Dummy variable indicating whether or not an individual had a fellowship one year prior to Ph.D.	0.609	0.602	*0.007*	0.674	0.688	*-0.014*
prepother	Dummy variable indicating whether or not an individual was anything other than full or part time employed one year prior to Ph.D.	0.671	0.765	*-0.101*	0.737	0.770	*-0.021*
alleng	Dummy variable indicating whether or not an individual's field of training was engineering	0.250	0.268	*-0.018*	0.131	0.116	*0.015*
astr	Dummy variable indicating whether or not an individual's field of training was astronomy	0.009	0.006	*0.003*	0.010	0.017	*-0.006*
agri	Dummy variable indicating whether or not an individual's field of training was in agriculture	0.039	0.049	*-0.010*	0.045	0.033	*0.012*
biol	Dummy variable indicating whether or not an individual's field of training was biology	0.274	0.240	*0.034*	0.372	0.428	*-0.056*
chem	Dummy variable indicating whether or not an individual's field of training was chemistry	0.108	0.090	*0.018*	0.121	0.102	*0.019*
comp	Dummy variable indicating whether or not an individual's field of training was computer science	0.043	0.038	*0.005*	0.034	0.015	*0.019*
earth	Dummy variable indicating whether or not an individual's field of training was earth science	0.030	0.029	*0.001*	0.029	0.036	*-0.007*
math	Dummy variable indicating whether or not an individual's field of training was mathematics	0.054	0.056	*-0.002*	0.072	0.031	*0.041*
medi	Dummy variable indicating whether or not an individual's field of training was medicine	0.133	0.163	*-0.031*	0.127	0.152	*-0.025*
phys	Dummy variable indicating whether or not an individual's field of training was physics	0.061	0.062	*-0.001*	0.059	0.070	*-0.011*
top110	Dummy variable indicating whether or not an individual received their Ph.D. from a top 110 institution	0.805	0.757	*0.049*	0.829	0.793	*0.036*
ru1Ph.D.	Zero-one dummy if Carnegie classification of school awarding degree is Research University I.	0.734	0.686	*0.048*	0.751	0.715	*0.036*
ru2Ph.D.	Zero-one dummy if Carnegie classification of school awarding degree is Research University II.	0.100	0.119	*-0.019*	0.101	0.092	*0.009*

doc1Ph.D.	Zero-one dummy if Carnegie classification of school awarding degree is Doctoral Granting I.	0.054	0.072	*-0.018*		0.042	0.054	*-0.012*
doc2Ph.D.	Zero-one dummy if Carnegie classification of school awarding degree is Doctoral Granting II.	0.048	0.054	*-0.006*		0.043	0.043	*0.000*
mediPh.D.	Zero-one dummy if Carnegie classification of school awarding degree is Medical school.	0.037	0.034	*0.003*		0.046	0.058	*-0.012*
elsePh.D.	Zero-one dummy if Carnegie classification of school awarding degree is anything other than RU1, RU2, Doc1, Doc2, or Medical.	0.024	0.032	*-0.008*		0.015	0.033	*-0.018*
public	Dummy variable indicating whether or not an individual received their Ph.D. from a Public Institution	0.689	0.711	*-0.022*		0.703	0.668	*0.035*
topfld	Dummy variable indicating whether or not an individual received their Ph.D. from an institution that was top ranked in their field of training.	0.646	0.588	*0.058*		0.664	0.637	*0.027*

A.3: MSA Data Sources

1. Hours of January sunlight, January temperatures, July temperatures, July relative humidity, and percentage of surface area covered by water come from Economic Research Service (E.R.S.) at the U.S. Dept. of Agriculture. E.R.S. offers data on climate for all counties in the continental U.S. The variables represent the mean from 1941-1970. For all MSAs with more than one county, the mean across each county within the MSA was taken. When more than one PMSA lies in one county (ie. NECMAs), the same values were given to each PMSA within that county.

2. Violent crime rates, number of park acres, commute times and percent Democratic were collected from the 1999 *Places Rated Almanac*, Savageau and D'Agostino. Violent crimes include murders, rapes, armed robberies, and aggravated assaults. The park measure includes all national forest, park, and wildlife refuge acres, plus state park units located within metro area counties.

3. Days with unhealthy air quality (days with an air quality index above 100) and number of superfund sites come from the U.S. Environmental Protection Agency (E.P.A.). The air quality index includes measurement on the following air pollutants: ground-level ozone, particle pollution (also known as particulate matter), carbon monoxide, sulfur dioxide, and nitrogen dioxide. If the AQI is above 100, it is unhealthy for sensitive groups.

4. Pupil to teacher ratios, student expenditures, and number of students come from the National Center for Education Statistics.

5. The Art and Entertainment Index was collected from the 1999 County Business Patterns Report. The measure includes the total number of establishments in MSA in 1999 with NAICS code 71 ('Arts, entertainment, & recreation'): Museums, Historical Sites, Zoos and Botanical Gardens, Performing Arts, Amusement, Gambling and Recreation Industries

6. Number of year colleges and universities was collected from Integrated Postsecondary Education Data System (IPEDS).

7. Number of utility patents was collected from U.S. Patent and trademark office.

8. MSA size, population density, percent with a bachelor's degree or higher, percent nonwhite, percent foreign born, and region indicators were collected from the 2000 U.S. Census Bureau.

A.4: MSAs by Region

East North Central

Akron, OH PMSA
Ann Arbor, MI PMSA
Appleton--Oshkosh--Neenah, WI MSA
Benton Harbor, MI MSA
Bloomington, IN MSA
Bloomington--Normal, IL MSA
Canton, OH MSA
Champaign--Urbana--Rantoul, IL MSA
Chicago, IL PMSA
Cincinnati, OH--KY--IN PMSA
Cleveland--Lorain--Elyria, OH PMSA
Columbus, OH MSA
Dayton--Springfield, OH MSA
Decatur, IL MSA
Detroit, MI PMSA
Eau Claire, WI MSA
Elkhart--Goshen, IN MSA
Evansville, IN--KY MSA
Flint, MI MSA
Fort Wayne, IN MSA
Gary--Hammond, IN PMSA
Grand Rapids-Muskegon-Holland, MI MSA
Green Bay, WI MSA
Hamilton--Middletown, OH PMSA
Indianapolis, IN MSA
Jackson, MI MSA
Janesville--Beloit, WI MSA
Kalamazoo-Battle Creek, MI MSA
Kenosha, WI PMSA
Kokomo, IN MSA
La Crosse, WI MSA
Lafayette--West Lafayette, IN MSA
Lansing--East Lansing, MI MSA
Madison, WI MSA
Mansfield, OH MSA
Milwaukee, WI PMSA
Muncie, IN MSA
Peoria, IL MSA
Racine, WI PMSA
Rockford, IL MSA
Saginaw--Bay City--Midland, MI MSA
Sheboygan, WI MSA
South Bend--Mishawaka, IN MSA
Springfield, IL MSA
Steubenville--Weirton, OH--WV MSA
Terre Haute, IN MSA
Toledo, OH MSA
Wausau, WI MSA
Youngstown--Warren, OH MSA

East South Central

Biloxi--Gulfport, MS MSA
Birmingham, AL MSA
Chattanooga, TN--GA MSA
Clarksville--Hopkinsville, TN--KY MSA
Decatur, AL MSA

Pacific

Anaheim--Santa Ana, CA PMSA
Anchorage, AK MSA
Bakersfield, CA MSA
Chico, CA MSA
Eugene--Springfield, OR MSA
Fresno, CA MSA
Honolulu, HI MSA
Los Angeles--Long Beach, CA PMSA
Medford, OR MSA
Modesto, CA MSA
Oakland, CA PMSA
Olympia, WA MSA
Oxnard--Ventura, CA PMSA
Portland--Vancouver, OR--WA PMSA
Redding, CA MSA
Richland--Kennewick--Pasco, WA MSA
Riverside--San Bernardino, CA PMSA
Sacramento, CA MSA
Salem, OR MSA
Salinas--Seaside--Monterey, CA MSA
San Diego, CA MSA
San Francisco, CA PMSA
San Jose, CA PMSA
Santa Barbara--Lompoc, CA MSA
Santa Cruz, CA PMSA
Santa Rosa--Petaluma, CA PMSA
Seattle, WA PMSA
Spokane, WA MSA
Stockton, CA MSA
Tacoma, WA PMSA
Vallejo--Fairfield--Napa, CA PMSA
Yakima, WA MSA

South Atlantic

Albany, GA MSA
Asheville, NC MSA
Athens, GA MSA
Atlanta, GA MSA
Augusta, GA--SC MSA
Baltimore, MD MSA
Charleston, SC MSA
Charleston, WV MSA
Charlotte--Gastonia--Rock Hill, NC--SC MSA
Charlottesville, VA MSA
Columbia, SC MSA
Cumberland, MD--WV MSA
Daytona Beach, FL MSA
Dover, DE MSA
Fayetteville, NC MSA
Florence, SC MSA
Fort Lauderdale--Pompano Beach, FL MSA
Fort Myers--Cape Coral, FL MSA
Fort Walton Beach, FL MSA
Gainesville, FL MSA
Goldsboro, NC MSA
Greensboro--Winston-Salem, NC MSA

Florence, AL MSA
Gadsden, AL MSA
Huntsville, AL MSA
Jackson, MS MSA
Jackson, TN MSA
Johnson City--Kingsport--Bristol, TN--VA MSA
Knoxville, TN MSA
Lexington-Fayette, KY MSA
Louisville, KY--IN MSA
Memphis, TN--AR--MS MSA
Mobile, AL MSA
Montgomery, AL MSA
Nashville, TN MSA
Owensboro, KY MSA
Pascagoula, MS MSA
Tuscaloosa, AL MSA

Mid Atlantic

Albany--Schenectady--Troy, NY MSA
Allentown--Bethlehem--Easton, PA--NJ MSA
Altoona, PA MSA
Atlantic City, NJ MSA
Bergen--Passaic, NJ PMSA
Binghamton, NY MSA
Buffalo--Niagara Falls, NY MSA
Dutchess, NY MSA
Erie, PA MSA
Glens Falls, NY MSA
Harrisburg--Lebanon--Carlisle, PA MSA
Jamestown--Dunkirk, NY
Jersey City, NJ PMSA
Johnstown, PA MSA
Lancaster, PA MSA
Middlesex--Somerset--Hunterdon, NJ PMSA
Monmouth--Ocean, NJ PMSA
Nassau--Suffolk, NY PMSA
New York, NY PMSA
Newark, NJ PMSA
Newburgh, NY--PA MSA
Philadelphia, PA--NJ PMSA
Pittsburgh, PA PMSA
Reading, PA MSA
Rochester, NY MSA
Scranton--Wilkes-Barre, PA MSA
State College, PA MSA
Syracuse, NY MSA
Trenton, NJ PMSA
Utica--Rome, NY MSA
Vineland--Millville--Bridgeton, NJ PMSA
Williamsport, PA MSA
York, PA MSA

Mountain

Albuquerque, NM MSA
Billings, MT MSA
Boise City, ID MSA
Boulder--Longmont, CO PMSA
Colorado Springs, CO MSA

Greenville--Spartanburg--Anderson, SC MSA
Hagerstown, MD MSA
Hickory--Morganton, NC MSA
Huntington--Ashland, WV--KY--OH MSA
Jacksonville, FL MSA
Jacksonville, NC MSA
Lakeland--Winter Haven, FL MSA
Lynchburg, VA MSA
Macon--Warner Robins, GA MSA
Melbourne--Titusville--Palm Bay, FL MSA
Miami--Hialeah, FL PMSA
Naples, FL MSA
Norfolk--Virginia Beach, VA MSA
Orlando, FL MSA
Panama City, FL MSA
Parkersburg--Marietta, WV--OH MSA
Raleigh--Durham, NC MSA
Richmond--Petersburg, VA MSA
Roanoke, VA MSA
Rocky Mount, NC MSA
Sarasota, FL MSA
Savannah, GA MSA
Tallahassee, FL MSA
Tampa--St. Petersburg--Clearwater, FL MSA
Washington, DC--MD--VA MSA
West Palm Beach--Boca Raton, FL MSA
Wheeling, WV--OH MSA
Wilmington, DE--NJ--MD PMSA
Wilmington, NC MSA

West North Central

Bismarck, ND MSA
Cedar Rapids, IA MSA
Columbia, MO MSA
Davenport--Moline, IA--IL MSA
Des Moines, IA MSA
Dubuque, IA MSA
Duluth, MN--WI MSA
Fargo--Moorhead, ND--MN MSA
Grand Forks, ND MSA
Iowa City, IA MSA
Joplin, MO MSA
Kansas City, MO--KS MSA
Lawrence, KS MSA
Lincoln, NE MSA
Minneapolis--St. Paul, MN--WI MSA
Omaha, NE--IA MSA
Rapid City, SD MSA
Rochester, MN MSA
Sioux City, IA--NE MSA
Sioux Falls, SD MSA
Springfield, MO MSA
St. Cloud, MN MSA
St. Joseph, MO MSA
St. Louis, MO--IL MSA
Topeka, KS MSA
Waterloo--Cedar Falls, IA MSA
Wichita, KS MSA

Denver, CO PMSA
Flagstaff, AZ-UT MSA
Fort Collins--Loveland, CO MSA
Grand Junction, CO MSA
Greeley, CO MSA
Las Cruces, NM MSA
Las Vegas, NV MSA
Phoenix, AZ MSA
Pocatello, ID MSA
Provo--Orem, UT MSA
Pueblo, CO MSA
Reno, NV MSA
Salt Lake City--Ogden, UT MSA
Santa Fe, NM MSA
Tucson, AZ MSA

New England

Bangor, ME MSA
Boston, MA--NH PMSA
Bridgeport--Milford, CT PMSA
Brockton, MA PMSA
Burlington, VT MSA
Danbury, CT PMSA
Fitchburg--Leominster, MA MSA
Hartford, CT PMSA
Lawrence--Haverhill, MA--NH PMSA
Lewiston--Auburn, ME MSA
Lowell, MA--NH PMSA
Manchester, NH MSA
Nashua, NH PMSA
New Bedford, MA MSA
New Haven--Meriden, CT MSA
New London--Norwich, CT--RI MSA
Pittsfield, MA MSA
Portland, ME MSA
Portsmouth--Rochester, NH-ME MSA
Providence--Warwick, RI--MA MSA
Springfield, MA MSA
Stamford--Norwalk, CT PMSA
Waterbury, CT MSA
Worcester, MA MSA

West South Central

Abilene, TX MSA
Amarillo, TX MSA
Austin, TX MSA
Baton Rouge, LA MSA
Beaumont--Port Arthur, TX MSA
Brazoria, TX PMSA
Brownsville--Harlingen, TX MSA
Bryan--College Station, TX MSA
Corpus Christi, TX MSA
Dallas, TX PMSA
El Paso, TX MSA
Fayetteville--Springdale, AR MSA
Fort Worth--Arlington, TX PMSA
Galveston--Texas City, TX PMSA
Houma--Thibodaux, LA MSA
Houston, TX PMSA
Killeen--Temple, TX MSA
Lafayette, LA MSA
Lake Charles, LA MSA
Lawton, OK MSA
Little Rock--North Little Rock, AR MSA
Longview--Marshall, TX MSA
Lubbock, TX MSA
Mcallen--Edinburg--Mission, TX MSA
Monroe, LA MSA
New Orleans, LA MSA
Odessa--Midland, TX MSA
Oklahoma City, OK MSA
Pine Bluff, AR MSA
San Antonio, TX MSA
Shreveport, LA MSA
Tulsa, OK MSA
Tyler, TX MSA
Waco, TX MSA
Wichita Falls, TX MSA

APPENDIX B

Supplement to Chapter 5

Table B.1

Wald Tests for Parameter Equality Across Sectors[1]

	CC 26, Draw 1	CC 26, Draw 2	CC 26, Draw 3
Variable	Wald Stat	Wald Stat	Wald Stat
CompCons	0.12	0.00	0.22
Distance	3.00	2.29	3.06
JanSun	13.43*	13.10*	13.06*
JanTemp	3.60	3.46	2.70
JulRH	4.27*	5.56*	5.42*
JulTemp	2.50	2.37	2.98
PWater	2.88	2.54	2.31
Coast	0.28	0.48	0.14
Vcrime	0.18	0.04	0.19
Parkacre	1.33	1.23	1.16
BadAQ	0.00	0.00	0.10
Supfund	6.53*	6.88*	6.94*
Art_Ent	5.44*	5.99*	3.50
Studexp	0.08	0.17	0.30
PupTeach	0.18	0.00	0.28
NStudnts	0.00	0.04	0.08
Comtime	6.74*	5.57*	4.68*
MSASize	1.72	1.56	1.34
PopDens	0.11	0.08	0.26
PerDem	0.55	0.57	0.36
PerBach	3.25	3.02	1.82
Pnonwhite	0.34	0.20	0.09
Pforborn	26.41*	22.30*	18.54*
HighEd	1.48	0.81	1.18
Pats	5.91*	7.03*	8.05*
NorthAtl	2.30	3.68	2.88
SouthAtl	1.67	2.05	2.71
NorthCen	2.44	3.24	2.45
Mount	0.10	0.01	0.05
Pacific	0.02	0.11	0.00

[1] Sub-samples: Permanent (Industrial Ph.D.s/Faculty) and Temporary (Postdocs)
*Indicates rejection of the null of equality at the 0.05 level of significance (critical value=3.85)

Table B.2

Summary Statistics for Variables Included In Sector Logit Equations

Variable Name	Definition	Industry Mean	FTAcad Mean	Postdoc Mean
ASC_Ind	Alternative Specific Constant for Industry	1.00	0.00	0.00
ASC_Acad	Alternative Specific Constant for FT Academe	0.00	1.00	0.00
ASC_Pdoc*	Alternative Specific Constant for Postdoc	0.00	0.00	1.00
Age	Age of the individual	32.31	36.04	31.77
Male	Dummy variable indicating whether or not individual is male	0.81	0.57	0.66
Citizen	Dummy variable indicating whether or not an individual is a U.S. citizen	0.55	0.82	0.61
Married	Dummy variable indicating whether or not an individual is married	0.61	0.62	0.54
Parent	Dummy variable indicating whether or not an individual has at least one child	0.44	0.44	0.35
Alleng	Dummy variable indicating whether or not an individual's field of training was engineering	0.53	0.18	0.11
Astr	Dummy variable indicating whether or not an individual's field of training was astronomy	0.00	0.01	0.01
Agri	Dummy variable indicating whether or not an individual's field of training was agriculture	0.02	0.04	0.03
Biol*	Dummy variable indicating whether or not an individual's field of training was biology	0.06	0.15	0.47
Chem	Dummy variable indicating whether or not an individual's field of training was chemistry	0.12	0.06	0.14
Comp	Dummy variable indicating whether or not an individual's field of training was computer science	0.08	0.09	0.01
Math	Dummy variable indicating whether or not an individual's field of training was mathematics	0.02	0.03	0.03
Earth	Dummy variable indicating whether or not an individual's field of training was earth science	0.05	0.15	0.04
Medi	Dummy variable indicating whether or not an individual's field of training was in a medical related field	0.04	0.26	0.08
Phys	Dummy variable indicating whether or not an individual's field of training was physics	0.07	0.03	0.07
Private	Dummy variable indicating whether or not an individual received their Ph.D. from a private institution	0.84	0.79	0.86
Top110	Dummy variable indicating whether or not an individual received their Ph.D. from a top 110 institution	0.32	0.26	0.32
Ru1Ph.D.	Zero-one dummy if Carnegie classification of school awarding degree is Research University I.	0.78	0.73	0.78

*Indicates the Benchmark or Control Group

Table B.3

Results From Nested Logit Equations
(Dependent Variable=Sector Choice)

	NL1 (N=18795)		NL2 (N=18795)	
Variable	Coeff.	t-stat	Coeff.	t-stat
IncVal	-0.320	-3.13	-0.278	-7.21
ASC_Acad	-4.204	-8.24	-0.953	-3.80
Acad*Age	0.080	15.34	0.051	11.53
Acad*Male	-0.263	-4.66	-0.078	-1.84
Acad*Citizen	1.206	20.16	0.457	11.99
Acad*Married	0.225	3.29	0.186	3.77
Acad*Parent	0.087	1.20	0.088	1.67
Acad*Alleng	2.283	27.98	2.102	41.65
Acad*Astr	0.843	3.26	0.775	4.00
Acad*Agri	1.460	11.61	1.216	11.34
Acad*Chem	0.603	6.10	0.827	13.61
Acad*Comp	3.695	27.39	2.870	31.69
Acad*Earth	1.459	10.37	1.163	10.04
Acad*Math	3.130	33.23	2.650	33.33
Acad*Medi	1.645	19.42	1.418	18.60
Acad*Phys	0.795	6.02	1.187	14.97
Acad*Top110	-0.186	-1.69	-0.061	-0.76
Acad*Private	-0.217	-3.87	-0.201	-5.14
Acad*Ru1Ph.D.	-0.042	-0.44	-0.112	-1.62
ASC_Ind	2.388	12.19	9.860	41.83
Ind*Age	-0.001	-0.28	0.013	2.92
Ind*Male	0.167	3.56	0.129	3.03
Ind*Citizen	0.150	3.67	0.196	5.14
Ind*Married	0.343	6.46	0.222	4.49
Ind*Parent	0.026	0.46	-0.015	-0.29
Ind*Alleng	3.824	58.36	3.331	65.09
Ind*Astr	1.155	5.74	1.081	5.58
Ind*Agri	1.825	16.77	1.412	13.16
Ind*Chem	2.020	30.19	1.487	24.43
Ind*Comp	3.986	32.76	3.364	37.09
Ind*Earth	1.962	17.26	1.716	14.82
Ind*Math	2.390	25.86	2.242	28.20
Ind*Medi	1.269	13.65	1.166	15.29
Ind*Phys	2.181	27.26	1.968	24.82
Ind*Top110	-0.080	-0.89	0.013	0.16
Ind*Private	-0.025	-0.61	0.017	0.42
Ind*Ru1Ph.D.	-0.081	-1.05	-0.077	-1.11
Log-Likeli	-14347.6		-14648.42	

Table B.4

Results From Generalized Nested Logit Equations
(Dependent Variable=Sector Choice)

	GNL1 (N=18795)		GNL2 (N=18795)	
Variable	Coeff.	t-stat	Coeff.	t-stat
IncVal	-3.073	-14.52	-0.853	-35.24
ASC_Acad	-4.153	-18.85	-2.939	-13.22
Acad*Age	0.078	14.86	0.078	14.49
Acad*Male	-0.269	-4.75	-0.270	-4.67
Acad*Citizen	1.144	19.08	1.075	17.66
Acad*Married	0.250	3.63	0.285	4.05
Acad*Parent	0.126	1.72	0.181	2.43
Acad*Alleng	2.280	27.91	2.351	28.32
Acad*Astr	0.790	3.04	0.772	2.89
Acad*Agri	1.542	12.21	1.682	13.09
Acad*Chem	0.597	6.03	0.610	6.07
Acad*Comp	3.705	27.39	3.824	27.82
Acad*Earth	1.386	9.82	1.385	9.58
Acad*Math	3.169	33.60	3.285	34.07
Acad*Medi	1.663	19.51	1.753	20.00
Acad*Phys	0.814	6.15	0.893	6.66
Acad*Top110	-0.255	-2.31	-0.328	-2.90
Acad*Private	-0.254	-4.51	-0.324	-5.63
Acad*Ru1Ph.D.	-0.045	-0.46	-0.069	-0.69
ASC_Ind	-0.390	-1.77	1.612	7.17
Ind*Age	-0.003	-0.51	-0.001	-0.11
Ind*Male	0.155	3.27	0.150	3.10
Ind*Citizen	0.101	2.45	0.072	1.70
Ind*Married	0.357	6.66	0.372	6.79
Ind*Parent	0.033	0.58	0.044	0.75
Ind*Alleng	3.845	57.94	3.887	57.41
Ind*Astr	1.118	5.46	1.141	5.38
Ind*Agri	1.898	17.23	1.983	17.74
Ind*Chem	2.030	29.95	2.035	29.36
Ind*Comp	4.050	33.02	4.190	33.65
Ind*Earth	1.905	16.47	1.901	15.92
Ind*Math	2.471	26.44	2.601	27.26
Ind*Medi	1.301	13.83	1.383	14.42
Ind*Phys	2.248	27.70	2.348	28.10
Ind*Top110	-0.082	-0.91	-0.058	-0.63
Ind*Private	0.131	3.04	0.262	5.91
Ind*Ru1Ph.D.	-0.117	-1.49	-0.141	-1.77
Log-Likeli	-14145.9		-13610.1	

APPENDIX C

Supplement to Chapter 6

Table C.1

Implicit Prices of City Attributes: All Models

Variable	Model 1: [A] Cond'l Logit (Spec 1)	Model 2: [B] Mixed Logit (Spec 1)		Model 3: [C] Cond'l Logit Hybrid	Model 4: [D] Mixed Logit Hybrid
JanSun	-47.1*	-1.7		-339.7*	-142.7*
JanSun Postdocs	n/a	n/a		37.4*	99.3*
JanTemp	512.3*	181.6		1148.3*	225.5*
JulRH	-527.3*	-582.2*		-960.3*	-876.0
JulRH Postdocs	n/a	n/a		-1205	-998
JulTemp	-861.0*	-959.9*		-1734.1*	-1063.3*
PWater	-164.8*	-87.0		-276.4*	-107.9
Coast	8156*	11696*		18326*	19253*
Vcrime	-3.2	1.9		1.6	6.3
Vcrime Parents	n/a	n/a		-32.8*	-23.9*
Parkacre	-111.9*	-110.0*		-230.4*	-164.9*
BadAQ	-232.2*	-157.7*		-481.7*	-331.9*
Supfund	131.1*	63.8		409.8*	203.0
Supfund Postdocs	n/a	n/a		106.7*	-7.9
Art_Ent	-48.6	-167.3*		-327.5*	-388.6*
Art_Ent Postdocs	n/a	n/a		330.7*	78.7*
Studexp	-1745*	-3686*		-2677*	-4943*
Studexp Parents	n/a	n/a		-13122*	-13931*
PupTeach	-589.0*	-743.1*		-1145.9*	-1150.2
PupTeach Parents	n/a	n/a		-1089.4	-968.7
NStudnts	-83.2*	-656.7		-554.9	-1400*
Nstudnts Parents	n/a	n/a		2693.8*	1153.0*
Comtime	-409.8*	-156.9		-1169.4*	-328.8
Comtime Postdocs	n/a	n/a		819.7*	1107.6*
MSASize	594.8*	722.5*		1259.2*	834.8*
PopDens	-1902*	-3754*		-5469.7*	-8077.3*
PerDem	67.9	52.3		75.9	69.9
PerBach	238.7*	503.8*		608.3*	744.0*
Pnonwhite	178.1*	92.7		1227.7*	952.1*
Pnonwhite White	n/a	n/a		-281.8*	-358.2*
Pforborn	629.0*	415.2*		3134.9*	2377.9*
Pforborn Citizens	n/a	n/a		1254.9*	845.9*
Pforborn Postdocs	n/a	n/a		1526.6*	1196.7*
HighEd	603.0*	597.5*		1095.4*	965.3*
Pats	139.2*	26.0		143.0*	7.6
Pats Industry	n/a	n/a		394.3*	141.0*

[*] Indicates that the estimated coefficient on the attribute was significant at the 10% level or better.
[A] Calculations are made from coefficients in Model 9 of simple conditional logit (Table 15).
[B] Calculations are made from coefficients in Model 3 of simple mixed logit (Table 17).
[C] Calculations are made from coefficients in Model 9 of hybrid conditional logit (Table 16).
[D] Calculations are made from coefficients in Model 3 of hybrid mixed logit (Table 18).

Table C.2

1997 Cragg/Kahn WTP Estimates vs. Our WTP Estimates
for Selected Climate Variables

Cragg and Kahn Estimates					Our Estimates			
Cragg/Kahn Variable	Mean Change	Range WTP Estimates*	Mean WTP Estimate*		Our Variable	Mean Change	Range WTP Estimates**	Mean WTP Estimate**
Hours of Jan Sunlight	8.1	$338 - $1,885	$1,045		Hours of Jan Sunlight	15.2	-$48 - -$726	-$387
Feb Temperature	10.4	$1,182 - $10,860	$5,263		Jan Temperature	3.7	$497 - $1,856	$1,177
July Temperature	5.2	-$984 - -$5,788	-$2,840		July Temperature	7.6	-$6,068 - -$6,495	-$6,218
July Humidity	10.3	-$846 - -$3,906	-$1,866		July Humidity	5.7	-$2,990 - -$3,246	-$3,118

* Range/Means represent estimates across all age cohorts for college educated individuals.
**Range/Means represent estimates across the conditional and mixed logit non-hybrid models.

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VITA

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While at Georgia State University, A.J. worked as a graduate research assistant and teaching assistant in the Economics Department. He was awarded the George J. Malanos Excellence in Economics Award and Scholarship in 2002 and the E.D. (Jack) Dunn Excellence in Finance Award and Fellowship in 2003. He served as president of the Graduate Student Association of the Andrew Young School from 2002 to 2003. He received his Master of Arts degree in Economics from Georgia State University in the Spring of 2003, and was awarded a dissertation fellowship from the Science and Engineering Workforce Project at the National Bureau of Economic Research in 2004. In August of 2005 he accepted a position as an Assistant Professor of Economics at Youngstown State University in Youngstown, Ohio.