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Applications of Regional Agglomeration: Measures of Localization and Urbanization

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APPLICATIONS OF REGIONAL AGGLOMERATION: MEASURES OF LOCALIZATION AND URBANIZATION

By

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An Abstract of the Thesis Presented
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Regional agglomeration, or the concentration of firms within a given locality, has been found to offer advantages, such as cost reductions, knowledge spillovers, and labor pooling, to firms and individuals who locate there (Malmberg & Maskell, 2002). Regional agglomeration is captured in two ways: localization economies and urbanization economies, where the former emphasizes the benefits of clustering of specific industries within a given geography while the latter a more general benefit of locating in regions with a high level of industrial activity (Bosma et al., 2008). This thesis dedicates a chapter to exploring each of these measures of agglomeration.

Chapter one of this thesis explores the caveats associated with measuring the impact of localization, also referred to as industrial clustering, in small rural places. Rural economies, due to the nature of their low urbanization level, are limited in the scope of their economic activities. In rural places, some economic policies encourage supporting industrial clusters in the region over other industries as a means of promoting economic growth. However, the precision of measures used to capture industrial localization, such as the location quotient (LQ), is dependent on the level of spatial and industrial aggregation. This chapter explores the extent to which industrial localization can be captured in small rural places (i.e. places with a high level of spatial aggregation) using an LQ and introduces a method of testing for LQ volatility. Through a model of new firm startups in Maine, the

implications of including small places with volatile LQs are revealed. Including small places where the LQs are volatile and therefore may not accurately capture industrial localization in that region conceals the effect of localization on these small rural places.

Chapter two of this thesis examines the benefits of urbanization on labor market job matching. The thick labor market fostered by urbanization economies can benefit workers by increasing the proximity of employment opportunities within their skillset (Duranton & Puga, 2003). Previous empirical studies have examined a link between urbanization and labor market matching, but primarily focused on larger metropolitan areas (Abel & Deitz, 2015; Büchel & Battu, 2003; Büchel & van Ham, 2003). This chapter expands upon the previous work conducted in the literature through an analysis of degree-level job matching of University of Maine alumni. Data from a 2020 survey of University of Maine alumni is used to gain an understanding of the employment prospects and location patterns of graduates. This analysis seeks to understand how regional characteristics, such as urbanization and localization, impact the likelihood of job match for UMaine graduates. The implications of job matching are evaluated through a Mincerian wage equation, where the wage premium of urbanization and job-matching is evaluated. The results show that the size of place, as measured by population in a locality, has a significant impact on job matching. This level of impact varies by industry and occupation. Furthermore, size of place has a large and significant impact on the wages of college graduates.

DEDICATION

I would like to dedicate this thesis to my friends and family. Without your support, encouragement, and understanding, I could not have made the sacrifices necessary to complete this thesis in a single academic year.

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Thank you to my mentors at the School of Economics and Margaret Chase Smith Policy Center for investing the time to provide support and guidance in matters both academic and personal. I truly attribute the knowledge and skills I have gained through my University of Maine experience to your patience and effort.

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Location Quotients	LQs
Dunn and Bradstreet	D&B
County Business Patterns	CBS
University of Maine	UMaine

CHAPTER 1

A SIMPLE APPROACH TO TESTING THE ROBUSTNESS OF LOCATION QUOTIENTS AS A MEASURE OF INDUSTRIAL LOCALIZATION IN SMALL RURAL PLACES

Location quotients (LQs) are a widespread and common method of identifying regional export industries (Artz et al., 2016; De Propris, 2005; Holl, 2004; Porter, 1998). LQs measure industrial localization at all levels of geography (e.g. county, state, etc). Studies have used LQs to characterize industrial agglomeration in cities (Glaeser & Gottlieb, 2009) and rural places (Artz et al., 2016; Gabe, 2003). Typically, an LQ of greater than one signifies industrial specialization relative to a benchmark. However, in rural places with small populations and only a handful of business establishments, large LQs may be misleading and not a clear indicator of industrial specialization. This may be problematic when using LQs to identify industry clusters in rural places because high values of LQs may not represent industry clusters that provide benefits to its incumbent firms and new entrants.

The first part of this chapter provides an overview of location quotients and their implementation in the literature as measures of industrial agglomerations. Using company data from Dunn and Bradstreet, the implications of naively using LQs to measure localization in small rural places is demonstrated. In the second part of this chapter, a methodology for correcting the LQ bias through the implementation of a population cutoff is demonstrated. A firm location model for the State of Maine is used to demonstrate this method.

Understanding the Location Quotient

Defining Location Quotients (LQs)

The location quotient (LQ) measures the importance of an industry in a region relative to its importance nationally (Miller et al., 1991). The LQ as a measure of industrial specialization was introduced in the late 1920s through Haig's economic base theory (EBT) model, which split regional economies into two sector groups: basic and non-basic sectors. Firms designated to the non-basic sector conducted business within their respective region whereas those within the basic sector exported goods outside the region. Although the LQ is most commonly calculated using employment data, its versatility as a measure of relative regional dominance allows flexibility for using establishment counts as well (De Propris, 2005; Guimarães et al., 2009). In work focused on labor pooling, an employment location quotient is preferred. Studies on new firm location generally opt for an establishment level location quotient (Artz et al., 2016; Capozza et al., 2018; Gabe, 2003).

An LQ for industry (i) in the region (r) is calculated by dividing the ratio of total employment or establishments within a given industry in a region by the same ratio at the national level (1.1).

$$LQ_{ir} = \frac{X_{ir}/X_r}{X_{iN}/X_N}$$

$$\begin{aligned} X_{ir} &= \text{industry i's employment (or establishment count) in region r} \\ X_r &= \text{total employment (or establishment count) in region r} \\ X_{iN} &= \text{industry i's employment (or establishment count) nationwide} \\ X_N &= \text{total employment (or establishment count) nationwide} \end{aligned} \tag{1.1}$$

An LQ can be interpreted as a measure of the amount of activity in a region's industrial sector relative to the national benchmark (Table 1-1). An LQ greater than one suggests specialization in the industry because the industry captures a larger share of regional activity than the national average for that industry.

Table 1-1: Interpretation of a Location Quotient (NY Division of Research and Statistics, 2017)

Location Quotient (LQ)	Interpretation
LQ > 1.00	Industry production above the national average; designated as export industry because production greater than local consumption
LQ = 1.00	Industry production equal to national average; production equal to local consumption
LQ < 1.00	Industry production less than national average; designated as an import industry because production less than local consumption

Capturing Industrial Agglomeration

Industrial agglomeration, localization, and spatial clustering, appearing near-interchangeably in the literature, denote the concentration of similar firms within a given locality (Malmberg & Maskell, 2002). The expansive advantages of industry agglomeration make it a crucial element to capture in spatial modeling. Malmberg and Maskell (2002) summarize the advantages of industrial agglomeration into several distinctive groups: cost reductions, and knowledge spillovers as a result of collocation. Knowledge spillover advantages are focused specifically on the industry-related information flow, learning, and innovation. Cost reduction advantages include reductions in production and maintenance costs from shared resources, such as infrastructure, educational systems (human capital training), and other resources that can be shared in a locality. The reduction in cost as a result of supply chain proximity is also a notable cost advantage (Porter, 1998, p. 199; Scott, 1983). Accessibility of labor with specialized skills is attributed as a cost advantage of industry agglomeration, as clustering acts as an incentive for skilled laborers to congregate in specific localities (Marshall, 1920).

Industrial agglomeration is captured most commonly in the literature in two ways: degree of localization and degree of urbanization (Bosma et al., 2008). Urbanization economies capture the benefits of locating in regions with high industrial activity, regardless of type, whereas localization economies capture high levels of activity within a specific industry (Frenken et al., 2005). Many studies on agglomeration have been centered around studying growth in metropolitan areas and urban places. Previous research identifies a distinct difference between urban and rural firms (Renski & Wallace, 2014), thus studying both is integral to understanding firm location decisions.

An area of research has emerged examining the existence of agglomeration economies in rural areas. Rural areas are highly diverse. The US Census Bureau designates any region with a population under 2,500 to be a “rural area”, meaning there is much diversity between rural areas (i.e. places just under 2,500 individuals relative to places with less than 50). Rural communities are encouraged, in some economic development plans, to support their industrial clusters over other industries in the area, as a means of promoting economic growth in their area (Barkley & Henry, 1997).

Localization, where it exists, has been found to be impactful on new firm entry in both urban and rural areas (Artz et al., 2016; Gabe, 2003). Kim et al. (2000) find that localization in non-metropolitan areas is impacted by firm structure characteristics, including the establishment size, labor intensity, labor shares of high and low skill workers, and importance of natural resource inputs. Jofre-Monseny et al. (2011) identify strong localization effects in industries who employ human capital with industry-specific skillsets, suggesting a high emphasis on the pooled labor force benefit from agglomeration.

LQs as a Measure of Industrial Agglomeration

Described in the work of Miller et al. (1991) as a measure of industry representativeness in a given region, it is fitting that the LQ was adopted as a standard measure of localization in spatial studies. The LQs popularity can be attributed to their simple nature and minimal data requirements relative to other metrics. LQs are most commonly used as measures of localization in two ways: defining the existence of industry clusters and comparing the degree of industrial specialization.

1. Defining the existence of industry clusters

The LQ is often used in congruence to other metrics for identification of industry agglomeration (i.e. industry clusters). In some studies, the LQ is calculated following a supply-chain analysis of the region, which allows for a more accurate grouping of clusters that exist outside of industrial groupings (Delgado et al., 2014a; Maine Center for Business and Economic Research et al., 2008; Resbeut & Gugler, 2016). When used to define existence of industry clusters, an LQ cutoff is typically implemented. A value of 1.0 is a commonly implemented, because an LQ greater than 1.0 signifies a greater regional share in the industry relative to the national level. However, different studies opt for different studies and this arbitrary use of cutoffs is a common criticism of LQs in the literature (Crawley et al., 2013; Martin & Sunley, 2003; O'Donoghue & Gleave, 2004). Table 1-2 depicts the variation in LQ cutoffs utilized in the literature to define the existence of a cluster.

Table 1-2: Arbitrary Cutoff Points Used for LQs

Papers	Cutoff
(Carroll et al., 2008; Held, 1996; Maine Center for Business and Economic Research et al., 2008; Tonts & Taylor, 2010)	$1 < LQ$
(Akgungor et al., 2003; De Propris, 2005; Delgado et al., 2014a)	$1.25 < LQ$
(Mendoza-Velazquez, 2017)	$1.5 < LQ < 2.5$
(Manzini & Luiz, 2019)	$2 < LQ$
(Isaksen, 1996)	$3 < LQ$

The degree of variance associated with LQ data inputs can skew the LQ, sometimes swaying the LQ across the cutoff-designated threshold (Crawley et al., 2013). The method of raw data collection, varying in technique from survey metrics to statistical inference, is ultimately an estimate of the original data. For example, at a low level of industrial aggregation, publicly available employment and establishment figures for a given year and industry may be imputed estimates rather than direct figures. It is crucial to consider the degree of variance associated with the LQ data inputs, particularly in small rural regions comprised of only a handful of establishments, because even miscounting by one company has the potential has the potential of shifting the size of the LQ over the arbitrary cutoff used to designate the existence of clustering.

Implementing standardizations and developing indices to overcome scale-sensitivity of the LQ is an alternative to an arbitrary cutoff (Carroll et al., 2008; Mulligan & Schmidt, 2005; Resbeut & Gugler, 2016). O'Donoghue and Gleave (2004) suggest implementing a standardized location quotient, which allows significance to be determined across different sample sizes by using a z-score to identify the appropriate cut-off for the sample. While standardization is able to control for the relative differences between the regional LQs, this methodology just swaps the use of a numeric cutoff to a proportion of the sample. Therefore, it is unable to prevent potential misrepresentation that LQs may have at a small regional level.

2. Comparing the degree of industrial specialization

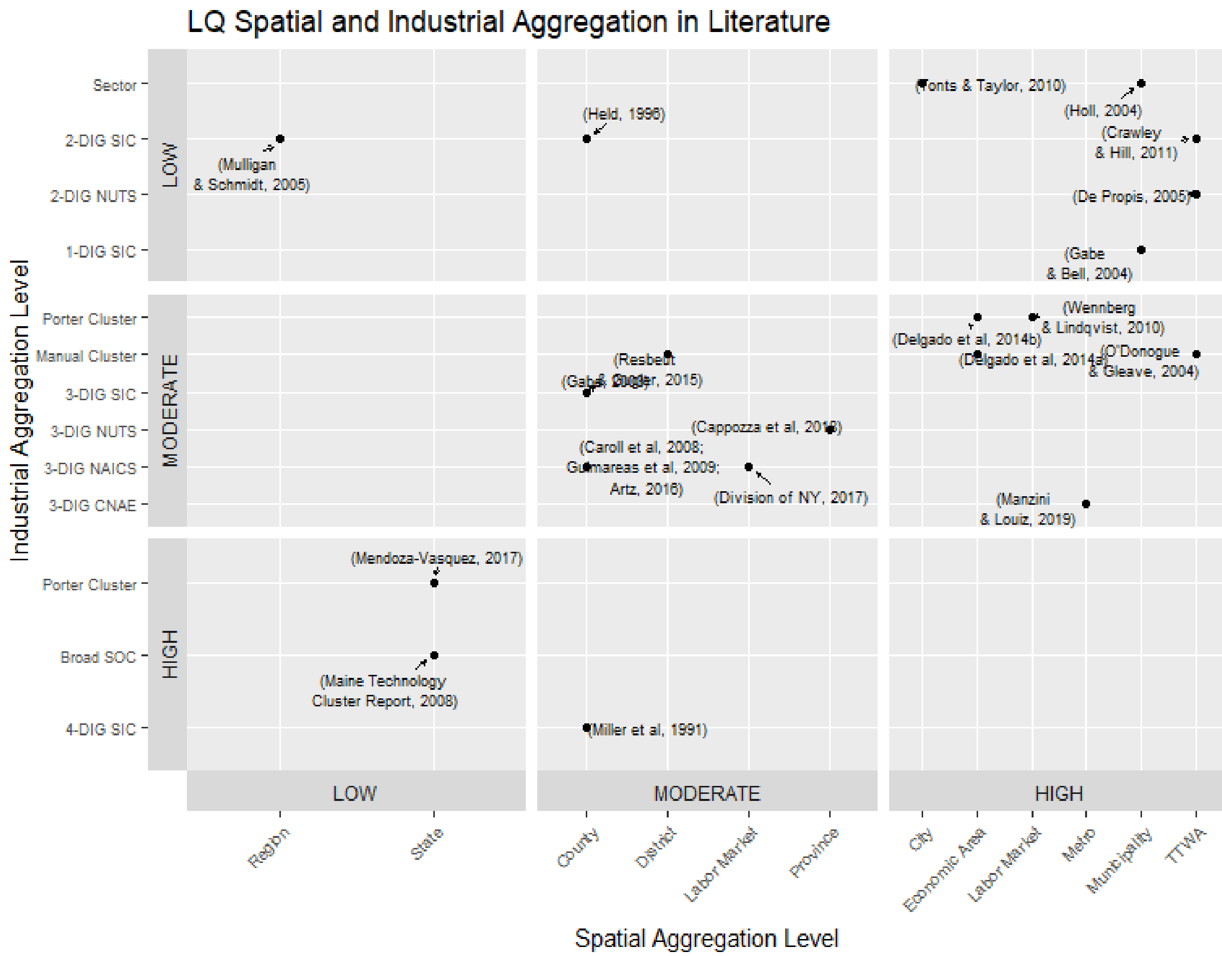
LQs can be implemented within a spatial model to cross compare industry agglomeration across sectors and regions, often either as continuous numeric variables or categorical dummies (Artz et al., 2016; Capozza et al., 2018; Delgado et al., 2014b; Gabe, 2003; Holl, 2004; Mulligan & Schmidt, 2005). While this method does not require the use of an arbitrary cutoff, this use of the LQ is also subject to scale sensitivity and data variance problems.

Wennberg and Lindqvist (2010) allude to the LQ's scale-sensitivity while testing between absolute and relative measures of agglomeration in their results, suggesting that, despite the LQ's strength for cluster identification, it is a weak measure for capturing the effect of variation in cluster strength. Fracasso and Marzetti (2018), on the other hand, conclude the LQ to be an unbiased metric, but caution that failing to properly control for overall size of local economic activity will result in a substantial bias. This inability of the LQ to control for absolute size of place can be mitigated through the use of a standardized location quotient (O'Donoghue & Gleave, 2004) or by comparing the local industry level to a sample of similarly sized regions, using a technique first introduced by Ullman and Dacey (1960). However, while Klosterman (1990) notes a benefit of looking at similar sized regions rather than the nation as a whole gives a fairer comparative, Pratt (1968) describes this technique as weaker than the traditional LQ.

The data variance limitation of the LQ is more challenging to overcome. The LQ requires single point-estimates for calculation but does not assess the degree of accuracy of these point estimates, which are subject to measurement error (Beyene & Moineddin, 2005). Billings and Johnson (2012) identify a tradeoff between aggregation level and statistical inference precision. The degree of spatial and industrial aggregation has generally been left up to the discretion of the researcher, with data availability often acting as the greatest limiting factor. There is no agreement in the literature on the optimal geographical boundaries. Thus, location studies vary extensively by size of spatial units and by industrial aggregation (Figure 1-1).

Decreases in spatial and industrial aggregation require a greater precision level in the data or more restrictive hypothesis testing in order to avoid biasing the LQ. For this reason, it is not recommended to calculate LQs with high degrees of spatial and industrial aggregation. Billings and Johnson (2012) suggest not using a degree of aggregation higher than a 3-digit NAICS code for county and zip-code level spatial aggregation. This poses a great challenge for researchers studying small rural places, as the high level of spatial aggregation limits the degree of industrial aggregation that can be studied and obtaining higher precision data is challenging, and maybe even impossible.

Figure 1-1: LQ Industrial and Spatial Aggregation Levels in Literature



Parsing out the degree to which the data's variance may be skewing the results is a limitation that has yet to be overcome in research on agglomeration in small rural places. This work aims to introduce a simple methodology for testing the robustness of the LQ at a high level of spatial aggregation

Testing the LQ in Small Rural Places

The construction of the LQ as a relative measure of an industry's presence in a region compared with a national benchmark might make it an unreliable indicator of industry localization in small rural places. When working with small rural places with a limited number of establishments but a small presence in several key industries, a large location quotient may not necessarily be indicative of actual specialization. A high LQ in such a region might be a true sign of a local industry cluster (e.g. providing benefits to existing companies and an attraction to new firms), or it might be a "false signal" due to the presence of one establishment in a small region.

To demonstrate the volatility of the location quotient in a small rural place, consider Table 1-3, which shows the 20 highest LQs calculated at the town-industry group level in Maine. This table is obtained from a dataset, described in more detail in the next section, with a high level of spatial aggregation and a moderate level of industrial aggregation. This dataset is comprised of 6,110 town-industry pairs: representing 13 industrial groups in 470 towns. The 13 industry groups are aggregated industry clusters specific to Maine[1]. (e.g. Environmental Services, Forestry-Related Products, and Medical Devices), consisting of as few as 3 and as many as 50 six-digit NAICS codes: a moderate level of industrial aggregation.

Although places with a population of 500 people or fewer represent 25% of towns in the dataset, they contain 47% of the LQs in Table 1-3. Isle Au Haut, for example, which has a population of less than 100 people and a total of 8 establishments, is home to the "largest" industrial cluster in the state. The Isle Au Haut Alternative Energy and Turbines cluster has a specialization 652 times the national average. In reality, the cluster consists of a single energy company which supplies power to the island. 65% of the most highly specialized industrial clusters in Table 1-3 consist of a single establishment. If that one company were to disappear, the LQ would drop from values excess of 100 to zero. Likewise, the LQ would change dramatically if the cluster were to grow by one establishment or simply if another establishment were to be added to the town.

[1] The industry clusters used in this study are aggregated by Bastille and Maine Technology Technology institute. They represent 13 industry groups that are dominant economic growth industries In the state of Maine.

Table 1-3: Top 20 LQs for Maine Town-Industry Groups

LQ	Industry Group	Town	Town Population	Industry Group Establishments
653	Alternative Energy and Turbines	Isle au Haut	61	1
574	Boatbuilding and Related Industries	Atkinson	249	2
539	Boatbuilding and Related Industries	Brooklin	858	7
475	Alternative Energy and Turbines	Atkinson	249	1
316	Boatbuilding and Related Industries	Cranberry Isles	123	1
263	Boatbuilding and Related Industries	Beals	485	1
218	Boatbuilding and Related Industries	North Haven	410	2
176	Boatbuilding and Related Industries	Long Island	239	1
163	Alternative Energy and Turbines	Parsonsfield	1,746	1
159	Alternative Energy and Turbines	Arundel	4,100	6
157	Agriculture, Aquaculture, Fisheries and Food Production	Westmanland	89	1
148	Forestry-Related Products	Carroll plantation	115	1
145	Alternative Energy and Turbines	Perry	825	1
142	Boatbuilding and Related Industries	Southwest Harbor	1,976	7
132	Boatbuilding and Related Industries	Sedgwick	1,137	2
127	Alternative Energy and Turbines	Exeter	1,012	1
122	Boatbuilding and Related Industries	Steuben	1,017	2
105	Boatbuilding and Related Industries	South Bristol	952	1
104	Alternative Energy and Turbines	Milford	3,054	1
99	Alternative Energy and Turbines	Cushing	1,415	1

To examine the stability of the LQs for the Maine town-industry pairs, an experiment can be performed where an additional establishment is added to each of the 13 clusters in a given town. Consider the previously discussed LQ for the Alternative Energy and Turbines cluster in Isle Au Haut. The breakdown of the LQ calculation is captured in (Equation (1.2).

$$LQ = \frac{X_{ir}/X_r}{X_{iN}/X_N} = \frac{1/8}{1{,}448/7{,}563{,}084} = 652.891 \tag{1.2}$$

Equation (1.3 depicts what would happen to the LQ for the town's Alternative Energy and Turbines cluster, if an additional establishment were added to each of the 13 clusters in Isle Au Haut.

$$LQ_{adj} = \frac{(X_{ir} + 1)/(X_r + 13)}{(X_{iN} + 1)/(X_N + 13)} = \frac{2/21}{1{,}449/7{,}563{,}097} = 497.098 \tag{1.3}$$

The adjusted LQ is approximately 31% smaller than the initial LQ. The substantial difference between the original and adjusted LQ calls into question whether reliable information on industrial agglomeration can be extrapolated at this level of industrial aggregation from Isle Au Haut. Squaring the difference between the original LQ and the adjusted LQ calculations (Equation 1.3) penalizes the larger differences in LQs and accounts for both positive and negative changes

$$DiffSq = (LQ_{adj} - LQ)^2 = 24{,}271.46 \tag{1.4}$$

Calculating the difference squared for each of the LQs in Isle Au Haut provides a basic overview of how volatile the LQ calculations are to small changes in establishment counts. Table 1-4 shows the difference squared for all the industry clusters located on Isle Au Haut.

Table 1-4: Volatility of LQs for Industry Clusters in Isle Au Haut

Industry Cluster	LQ	adjLQ	diffSq
Alternative Energy and Turbines	653	497	24,165
Agriculture, Aquaculture, Fisheries and Food Production	20	15	22
Biopharmaceuticals	0	40	1,603
Boatbuilding and Related Industries	0	150	22,631
Defense	0	87	7,630
Electronics and Semiconductors	0	34	1,155
Engineering and Scientific/Technical Services	0	4	18
Environmental Services	0	13	166
Finance and Business Support Services	0	1	1
Forestry-Related Products	0	7	50
Information Technology Services	0	2	5
Materials for Textiles, Apparel, Leather and Footwear	0	9	87
Medical Devices	0	58	3,348

The average difference squared for the LQs across all industry clusters in Isle Au Haut is 4,683, meaning that on average the LQs for each cluster change by 68 when the clusters are increased by a single establishment. This suggests that LQs may not be a reliable indicator of industry specialization in this locality.

To examine the stability of the LQs in towns of all sizes, a similar analysis is conducted for all 6,110 town-industry pairs in Maine. Business location data from Dunn and Bradstreet (D&B) dataset is used to obtain company counts at a town level for each of the 13 aggregated industry sectors[2]. An LQ is calculated for each sector and region: the numerator is comprised of D&B companies founded in 2014 or earlier and the denominator using 2014 US level industry data (Equation (1.5).

$$LQ_{cr} = \frac{X_{cr}/X_r}{X_{cN}/X_N} \tag{1.5}$$

Next, an adjusted location quotient is calculated for each sector and region by adding a single new company in each sector to each region (Equation (1.6).

$$LQ_{adj} = \frac{(X_{cr} + 1)/(X_r + 13)}{(X_{cN} + 1)/(X_N + 13)} \tag{1.6}$$

Lastly, the average difference squared between the original and adjust LQ is used to test the robustness of the LQs in each region (Equation (1.7).

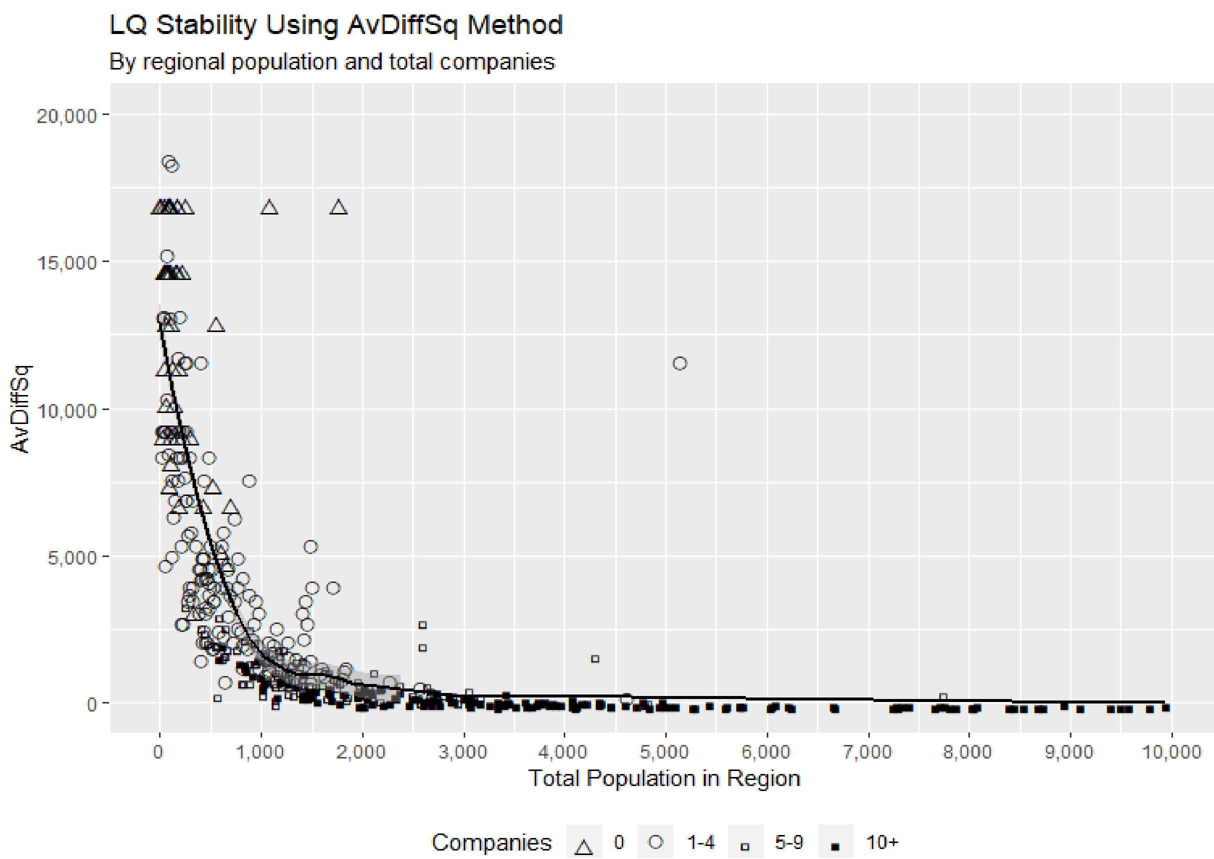
$$AvDiffSq = \frac{\sum_c \left(LQ_{adj} - LQ\right)^2}{13} \tag{1.7}$$

Figure 1-2 shows the average stability of the LQ for each region, captured by AvDiffSq, relative to the size of the region. As the size of the region increases, in both population and number of companies, the volatility of the LQ decreases to zero. For rural regions (i.e towns with a population less than 2500), there is always some degree of volatility with the LQ, compared to urban regions. The smaller the region the more unstable the LQ becomes.

[2] The D&B data for Maine consists of 57,735 establishments, 6747 (11%) of which are in one of the 13 aggregated industry sectors. Of the 6,747 establishments, 5,821 (86%) were founded prior to 2014.

For towns with more than 500 people, the experiment changed the LQs by less than 16, on average, with the arbitrary addition of an additional establishment to each of the 13 clusters. For towns with fewer than 500 people, on the other hand, the LQs changed by an average of 55. The very large changes in the LQs in towns with fewer than 500 people suggest that the LQ might be an inaccurate measure of industry agglomeration at a town level of geography. Including these small places may result in an inaccurate representation of market responsiveness to industrial localization.

Figure 1-2: Stability of the Location Quotient Using the AvDiffSq Method



Using a dataset comprised of places where LQs exhibit a high degree of volatility might reduce the utility of using LQ for identifying industry clusters as well as in studies that analyze the effects of industry agglomeration on regional growth. The next section of this chapter demonstrates the degree to which including LQs from high-volatility places alters the market responsiveness to agglomeration in a model analyzing location decisions of business in Maine.

Industrial Clustering and Innovation in Maine

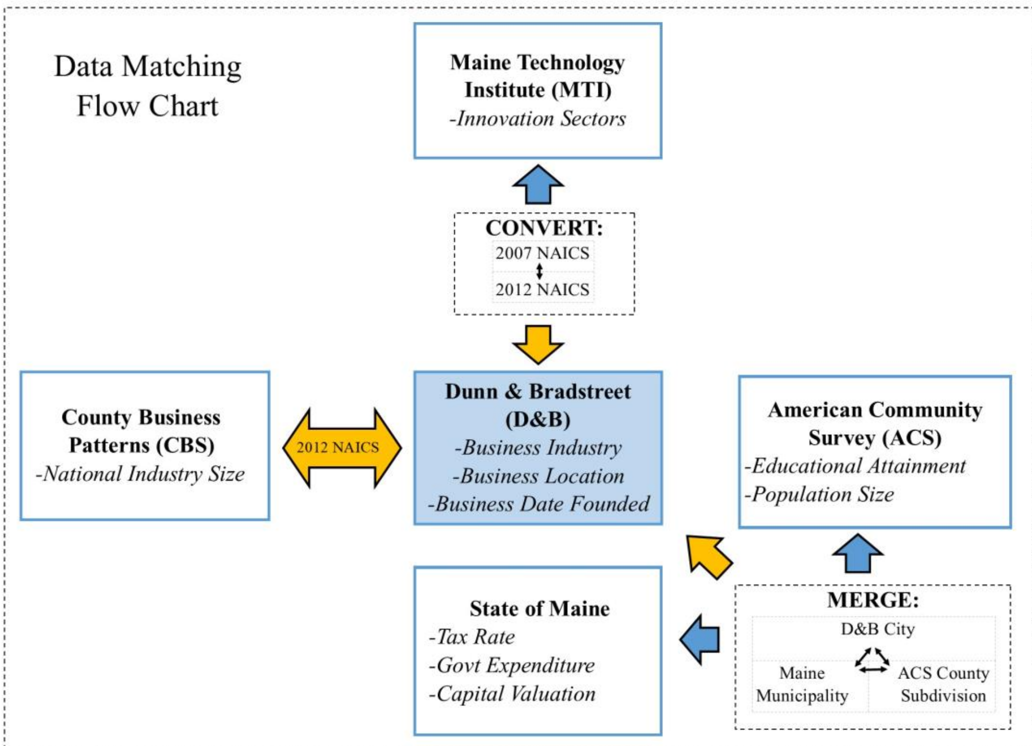
The extensive benefits of regional agglomeration, such as knowledge sharing and cost reductions from shared resources, supply chain proximity, and labor pooling, serve as an incentive for new firm entry (Malmberg & Maskell, 2002; Marshall, 1920; Porter, 1998; Scott, 1983). Within-industry agglomeration (i.e. localization) has been found linked to increased entrepreneurship, a benefit of knowledge-sharing (Nyström, 2005). Localization in industries with an industry-specific labor force suggests a demand for labor pooling as well (Jofre-Monseny et al., 2011). Understanding the link between agglomeration and new firm entry for the state of Maine could help inform policy decisions to help improve Maine's economic well-being.

Previously, localization economies and their effect on new firm formation has been studied at a county level in Maine (Gabe, 2003; Gabe & Bell, 2004). However, it is bold to assume that industrial composition of the towns within each Maine county is homogenous. For example, Aroostook county, the largest and northernmost county in Maine, is the size of Connecticut and Rhode Island combined. However, studying localization at a higher level of spatial aggregation would require a more cautious approach to the measures used to model it. Using LQs to measure localization without controlling for their volatility in some places may mask the effect of localization on firm location decisions. The effect of the small places with volatile LQs on modeling the relationship between industrial agglomeration and new firm location is demonstrated through the creation of a model for the number of new business startups in Maine towns.

Data

A dataset is constructed for every Census county-subdivision in Maine capturing new business entry in the 13 technology clusters recognized by the Maine Technology Institute (MTI) based on various characteristics. The dataset is comprised of data from 5 different sources, matched based on common identifiers (Figure 1-3).

Figure 1-3: Maine Innovation Model Data Flow Chart



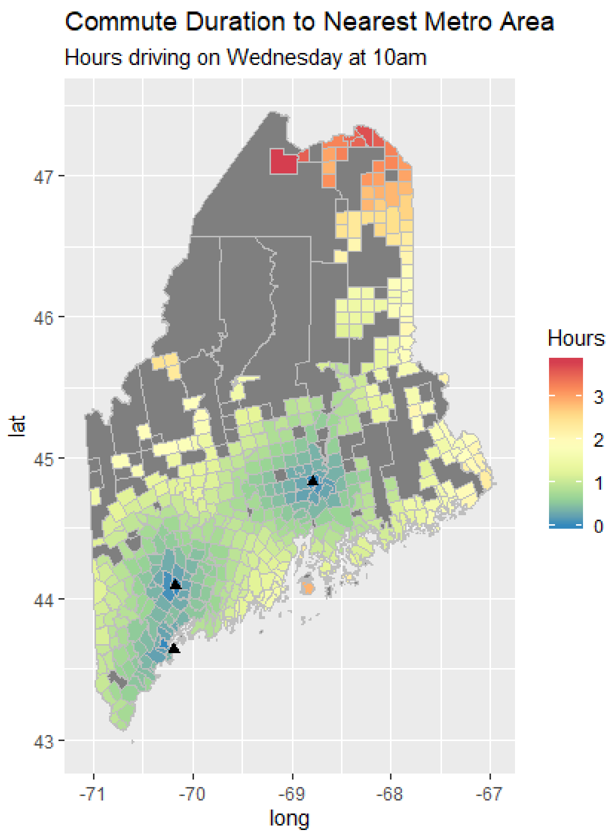
Business location data from a 2017 Dunn and Bradstreet (D&B) dataset is used to obtain company count data on Maine's businesses. Company counts are filtered into the 13 technology clusters in Maine, as recognized by the Maine Technology Institute (MTI) and Battelle (Table 1-5). These clusters consist of as few as three 3 and as many as 50 six-digit NAICS codes, based on mutual supply chains, technological competencies, markets, and their role in the state's economy (Battelle Technology Partnership Practice, 2014). D&B companies within Maine's innovative clusters are divided into two groups based on the date they were founded: new companies (founded in 2014 or later) and existing companies (founded prior to 2014). Regional characteristics and fiscal policy data on the Census county subdivisions are obtained from the American Community Survey (ACS) and the State of Maine for the year 2014, to control for conditions at the time of entry.

Table 1-5: Companies Founded Before 2014 by Maine Technology Cluster

Maine Technology Cluster	Total Companies
Agriculture, Aquaculture, Fisheries and Food Production	1933
Alternative Energy and Turbines	92
Biopharmaceuticals	62
Boatbuilding and Related Industries	100
Defense	29
Electronics and Semiconductors	51
Engineering and Scientific/Technical Services	488
Environmental Services	428
Finance and Business Support Services	1814
Forestry-Related Products	658
Information Technology Services	486
Materials for Textiles, Apparel, Leather and Footwear	187
Medical Devices	54

To further control for spatiality, distance to the nearest metropolitan area (i.e. Portland, Lewiston, and Bangor) are calculated using the Google API mapping software. The distances are calculated from the centroid of each town in minutes it would take to drive there on a Wednesday at 10am. Figure 1-4 graphically shows the commute distance, rounded up to hours, for each of the towns in the dataset

Figure 1-4: Distance from Nearest Metro Area



Methodology

Market responsiveness to agglomeration is modeled through an analysis of new firm entry in each town-industry pair. New firm entry is commonly studied using a Poisson regression model, a specification that can be used with count data (Wu, 1998). The probability of new firm entry in a given town-industry group of being equal to a nonnegative integer value $\mathrm{y_i}$ is captured in Equation (1.8).

$$Prob(Y_{it} = y_{it}) = {\exp(-\lambda_{it})\, \lambda_{it}^{y_{it}}} \Big/ {y_{it}!} \ , \quad \lambda > 0, \mathrm{y_i} = 0, 1, 2, \dots, \mathrm{n} \qquad (1.8)$$

$$\mathrm{Y_{it}} = new\ firm\ entry\ in\ industry\ i\ and\ town\ t$$

$$\lambda_{\mathrm{it}} = mean\ firms\ in\ industry\ i\ and\ town\ t$$

The mean number of firms in the town-industry group is a log-linear function of the explanatory variables (Equation (1.9).

$$\ln(\lambda_{it}) = \beta_0 + \sum_{j=1}^{k} \beta_j X_{itj} \tag{1.9}$$

$\lambda_{\text{it}} = mean\ firms\ in\ industry\ i\ and\ town\ t$

$X_{\text{itj}} = explanatory\ variable\ j\ describing\ town - industry\ pair$

The Negative Binomial regression model is an extension of the Poisson specification which allows for variance that differs from the mean and is commonly implemented when the data is overdispersed (Alañón-Pardo & Arauzo-Carod, 2013; Gabe & Bell, 2004). The probability of new firm entry in a given town-industry group is captured in Equation (1.10).

$$Prob(Y_{it} = y_{it}) = \frac{\Gamma(\mathrm{y}_{\mathrm{it}} + \alpha)}{\Gamma(y_i + 1)\Gamma(\alpha)} \left[\frac{\alpha}{\alpha + \mu_i}\right]^{\alpha} \left[\frac{\mu_i}{\alpha + \mu_i}\right]^{yi} \tag{1.10}$$

$\Gamma = \ gamma\ function\ (i.e. \Gamma(\mu_i, \alpha)\ )$

After testing for overdispersion, a Negative Binomial regression model is selected for this analysis. The dependent variable, new firm entry (new_companies) in each town-industry pair is captured using the D&B new companies founded in 2014 or after. The decision of market entry is made based on local market factors and regional growth, conditions new firms who could locate anywhere are aware of but unable to influence, thus helping control for that identification problem (Artz et al., 2016; Jofre-Monseny et al., 2011). In this model, new firm entry is a function of industrial agglomeration and regional characteristics. Industrial agglomeration is captured using location quotients, calculated for each technology cluster and town, using D&B existing company data for the numerator and 2014 CBP data for the denominator. An LQ is calculated for each town-industry group.

Controls for regional characteristics include urbanization, human capital, and fiscal policy. Urbanization is controlled for through the natural log of regional population size (Holl, 2004; List &

McHone, 2000). Human capital heterogeneity is captured through a measure of the concentration of college graduates in the region (ed_higher_p) (Arauzo-Carod et al., 2010; Artz et al., 2016). Fiscal policy, shown to be impactful on new firm location, are included in the form of tax rate (taxrate) and per capita government expenditure (govspending) (Gabe & Bell, 2004; Head et al., 1999). Dummy variables for each innovative cluster are included to control for variation across innovative cluster on the impact of agglomeration on new firm entry. Location quotients are interacted with the dummies to identify the marginal effects. County-level dummies and the distance to the nearest municipality (distmun) are included to control for spatiality.

Summary statistics and variable descriptions for model variables are shown in Table 1-6 and pairwise correlations between the variables in Table 1-7.

Table 1-6: Descriptive Statistics

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
new_companies	Number of companies founded between 2014 and 2017 in the town-industry group	6110	.14	.91	0	50
lnpop	Natural log of population in the town	6097	7.05	1.42	2.4	11.1
ed_higher_p	Percentage of town population with a bachelor's degree or higher	6097	.32	.12	0	.73
taxrate	Town tax rate	6110	.02	.01	0	.03
govspending	Town government spending per capita	6097	2,026.39	2,531.19	48.06	44,502.29
distmun	Distance (minutes driving) to the nearest municipality	6019	69.16	42.97	0	226.97
cluster	Dummy variable for the industrial group	6110				
County	Dummy variable for county in Maine	6110				
lq	Location Quotient for the town-industry	6110	2.8	18.34	0	652.89

Table 1-7: Pairwise Correlations

Variables	new_com~	ln_pop	ed_hig~	taxrate	govspe~	distmun	cluster
lnpop	.20***	1					
ed_higher_p	.12***	.34***	1				
taxrate	.06***	.27***	-.25***	1			
govspending	-.01	-.27***	.27***	-.16***	1		
distmun	-.11***	-.47***	-.27***	.06***	.05***	1	
cluster	-.04***	.00	.00	.00	.00	.00	1
lq	.01	-.02	.02	-.02	.03**	.01	-.12***

Results and Discussion

The results of the negative binomial model are captured in Table 1-8. Complete model results are shared in APPENDIX 1A: COMPLETE MARGINAL EFFECTS OF BUSINESS EFFECTS FOR BUSINESS STARTUP MODEL. The table shows the marginal effects of increases in the explanatory variables, including the LQ, on number of new firms in the town-industry groups.

Table 1-8: Marginal effects from NB Model on New Establishment Count

	(1)	(2)	(3)	(4)	(5)
	No Cutoff	100 Cutoff	250 Cutoff	500 Cutoff	1000 Cutoff
lnpop	**0.15*****	**0.15*****	**0.17*****	**0.19*****	**0.23*****
	(12.52)	(12.33)	(11.90)	(11.74)	(10.96)
ed_higher_p	**0.27*****	**0.27*****	**0.30*****	**0.32*****	**0.35*****
	(3.65)	**(3.50)**	**(3.53)**	**(3.27)**	**(2.96)**
TaxRate	2.41$^{\cdot}$	2.48	3.05$^{\cdot}$	**3.66***	3.91$^{\cdot}$
	(1.48)	(1.44)	(1.60)	(1.72)	(1.55)
govspending	-0.00	-0.00	-0.00	-0.00	-0.00
	(-1.09)	(-0.71)	(-0.74)	(-0.26)	(-0.35)
distMun	0.00	-0.00	-0.00	-0.00	0.00
	(0.05)	(-0.02)	(-0.35)	(-0.21)	(0.07)
LQ	**0.05*****	**0.06*****	**0.07*****	**0.08*****	**0.09*****
	(4.86)	**(4.10)**	**(4.06)**	**(3.97)**	**(3.79)**
Observations	6006	5642	5135	4589	3692

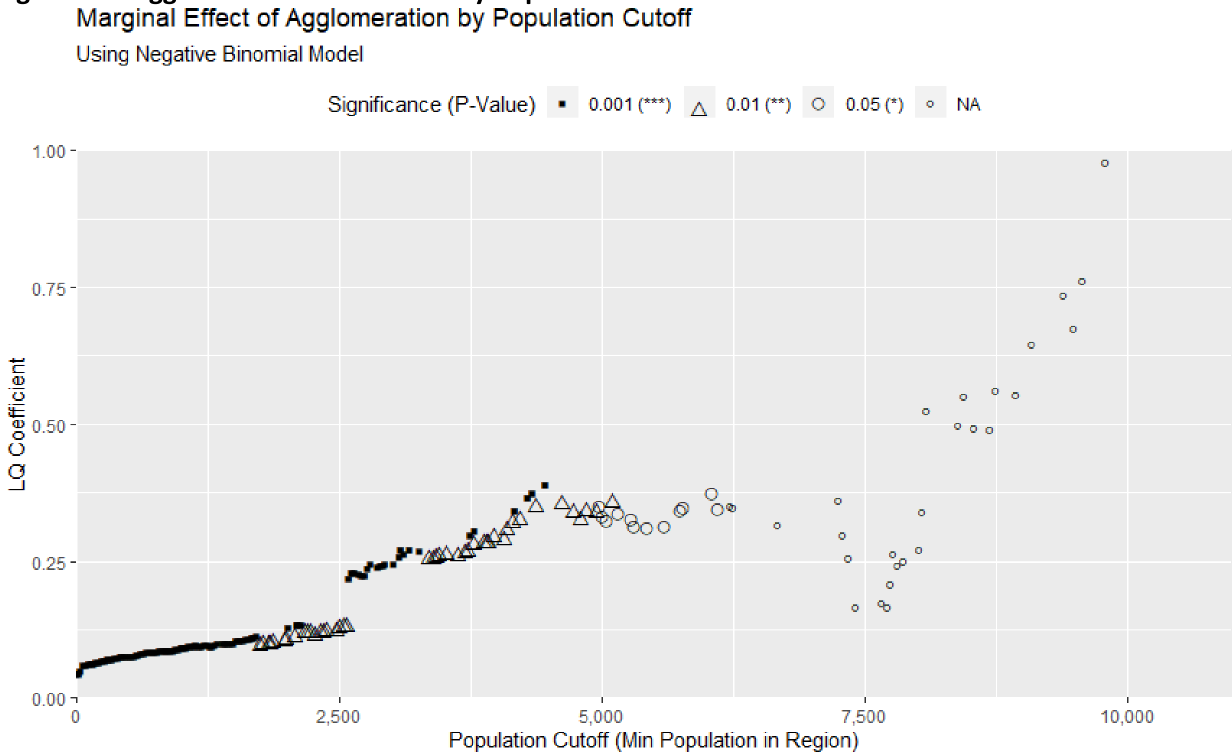
t statistics in parentheses
Robust standard errors
Hidden controls: county and cluster dummies
$^{\cdot}$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The first panel captures the results, without no population cutoff. As shown in the first column of results, the industry location quotient has a positive and statistically significant effect on the number of new business start-ups per sector-town combination. For example, a one unit increase in location quotient has a marginal effect of a 0.05 increase in new startups over the 3-year period. In addition, the regression results show that urbanization level and the town’s college attainment rate both also have a positive effect on number of new business startups. A percentage point increase in population size increases the number of new establishments in the town-cluster group by 0.15, whereas the proportion of the population with a college degree or higher increases the number of new establishments in the town-cluster group by 0.27.

In order to examine the influence of including observations from very small places, where the LQ may be an unreliable indicator of local industry specialization, the business start-up model is re-estimated using several population cut-off thresholds. For example, a population cut-off of 100 people removes from the sample the 32 smallest places in Maine (6.8% of the dataset), whereas a cut-off of 1,000 people removes 186 places in Maine (39.6% of the dataset). Panels 2 – 5 compare marginal effects to the business startup model when population cutoffs are implemented in the highly-volatile LQ range of under 1,000 people that was depicted in Figure 1-2. The highly educated proportion of the labor force, urbanization, and industrial localization of the region remain significant in all iterations of the model. The standard errors for all the significant coefficients decrease as larger population cutoffs are implemented.

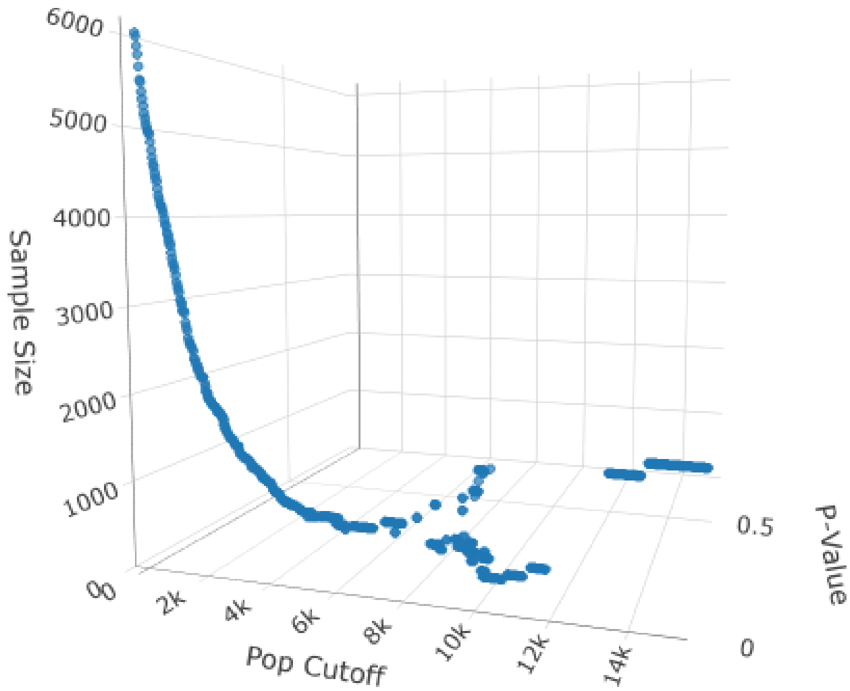
The LQ is significant at a 1%, regardless of cutoff level, however, the significant of the coefficient increases as the cutoff is introduced. With no cutoff implementation, a 1 unit increase in LQ increases the number of companies founded in a cluster town pairing by 0.05. Implementing a population cutoff of 100, increases the effect by 0.01. At a population cutoff of 1,000, the population cutoff at which the average difference squared begins to level out in Figure 1-3, a one unit increase in LQ increases the number of companies founded in the town-cluster pairing by 0.09.

Figure 1-5: Agglomeration Coefficient by Population Cutoff



Observing this effect over a span of cutoffs increasing by increments of 25 yields an interesting result (Error! Reference source not found.). As the cutoff increases, the marginal effect of the LQ Coefficient also increases. However, at a population cutoff of about 2,000, the significance level begins to decrease. This is because the size of the sample decreases to the point where statistical inference becomes more challenging (**Error! Not a valid bookmark self-reference.**). Identifying an appropriate cutoff point requires a balance between removing regions that are too small and ensuring that the sample still contains enough observations to remain meaningful.

Figure 1-6: Tradeoff between the Sample Size, Population Cutoff, and Significance of the LQ Marginal Effect



Up to a population of about 2000, there is clear linear growth in the size of the LQ marginal effect suggesting that the effect of localization on new firm entry may be masked by the volatile location quotients. However, there is a tradeoff between low volatility in the LQs and sample size. Creating a model measuring the effect of localization on new firm entry in Maine requires an artful balance between population cutoffs and maintaining a large enough sample size for preserving explanatory power. A population cutoff too steep could change the meaning behind the model. At a population cutoff of 2500, the model is no longer capturing the effect of agglomeration on small rural places, given that the definition of rural is a place with a population of under 2500.

It is ultimately up the researcher's discretion what level of aggregation to use. It is not recommended to use a level of industrial aggregation above "moderate" when working with rural places, as that may result in a very low total cluster count and could skew the calculations, as demonstrated in this example with Maine town-cluster pairings. In the example demonstrated in this chapter, a moderate level of industrial aggregation and high level of regional aggregation, an average difference squared of under 1500 for all regions required a population cutoff of 1000, resulting in a 38.5% decrease in sample size but increasing the effect of localization on new firm entry by 4 percentage points. A more volatility-tolerant cutoff of 500 resulted in a decrease in sample size of 23.6% but an increase in the effect of localization on new firm entry of 3 percentage points.

Some rural economic development plans recommend prioritizing investment of public funds in industrial clusters over other industries as a means of promoting economic growth in the region (Barkley & Henry, 1997). For small towns in Maine, the policy implications of identifying a strong effect between localization and new firm entry could include shifting investments to support an entirely different set of industries. Controlling for the highly volatile LQs resulted in an increase in localization effect of 80%. This is significant when making policy decisions regarding supporting industrial clusters.

Conclusion

This paper provides an overview of location quotients (LQs) as a measure of localization and discusses the caveats of using LQs in economic modeling when working with small rural places. This paper demonstrates a methodology for testing the robustness of an LQ for small rural places by adding an arbitrary company to each industry and recalculating the LQ for each town-industry pair, determining whether or not the town should be included by examining the average difference squared between the two LQ calculations. The paper then demonstrated the usefulness of this robustness check, showing that at moderate level of industrial aggregation and high level of regional aggregation, the effect of localization on new firm entry could range anywhere from 5 percentage points to over 10 percentage points, depending on the population cutoff that was implemented. By using average difference squared to guide the population cutoff decision that both minimizes LQ volatility and maximizes sample size, the skew associated with LQs for small rural places can be minimized.

The findings in this paper contribute to the literature by providing a simple robustness check for location quotients when working with small rural places. A preliminary examination of the data, with an implementation of the average difference squared method, and a check of model results by varying population cutoffs, as demonstrated in this chapter, may help assess and control for the volatility of LQs. Given the policy implications of findings regarding industrial clusters and regional economic growth, ensuring that the results capture the true effect and not a biased one is crucial to the success and prosperity of these regions.

CHAPTER 2

THE ROLE OF REGIONAL AGGLOMERATION AS A DETERMINANT OF EDUCATIONAL MISMATCH IN COLLEGE GRADUATES

In 2018, 32% of United States residents over the age of 18 have completed a bachelor's degree or higher: the highest educational attainment in the country to date (CPS, 2018). Yet, as educational levels continue to rise, overeducation, a form of educational mismatch categorizing individuals employed in fields that require a lower level of degree than they attained, is becoming an ever more prevalent problem in labor markets across the world (P. J. Sloane et al., 1999; Tsang & Levin, 1985; Wronowska, 2017).

Regional and urban economists have documented a variety of benefits associated with large urban areas. Duranton and Puga (2003) classify the sources of these benefits using a typology of sharing, matching and learning. A key aspect of the urbanization benefit of matching is that large urban areas provide a thick labor market that helps workers find a job that provides a good match to their skills and education. Several empirical studies have examined the role of urbanization on labor market job matching (Abel & Deitz, 2015; Büchel & Battu, 2003; Büchel & van Ham, 2003).

By using data from a 2020 survey of University of Maine alumni, this chapter aims to strengthen the understanding of the relationship between a region's size and labor market match. This paper adds to previous literature by expanding upon the size of place parameter in the data: looking at both small and large counties. A stronger understanding of the determinants of job matches in college graduates can be beneficial not only to college students, who aim to graduate and enter the labor force, but also to institutions for improving the educational foundations and job-prospects of their programs.

Educational Mismatch in the Literature

Educational mismatch, defined as the lack of a match between a laborer's educational attainment level and the job's educational requirements, was first introduced to labor economics by Freeman (1976). Educational mismatch in college graduates is most commonly evaluated at degree level (Abel & Deitz, 2015; Groot & Maassen van den Brink, 2000; McGoldrick & Robst, 1996; Peter J. Sloane, 2014) but can also be evaluated at more specific college field of study (i.e. college major) level (Abel & Deitz, 2015; Marin & Hayes, 2017; Robst, 2008). While educational mismatch encapsulates both undereducation and overeducation, educational mismatch in college graduates is almost exclusively the latter. In this paper, educational mismatch refers to the overeducation of individuals at a degree-level and job match captures the inverse, or lack of, overeducation.

Educational mismatch in college graduates has been studied in nations across the world, with the majority of the studies concentrated in the European Union (Croce & Ghignoni, 2015; Davia et al., 2017; Dolton et al., 2001; Morgado et al., 2016; Reimer et al., 2008), but representation in the US (Abel & Deitz, 2015; Clark et al., 2017; Freeman, 1976), Russia (Kyui, 2010; Shevchuk et al., 2015), Australia (Peter J. Sloane, 2014) and other nations as well. While the studies on educational mismatch span numerous counties, encompass various calculations of overeducation, and analyze both time series and panel data, there is consistency across the causes, determinants, and consequences of educational mismatch. To better understand the link between spatiality and educational mismatch in college graduates, this chapter will first discuss the methods used to measure educational mismatch, review the theories for why it takes place, and discuss the determinants of educational mismatch and their relationship with spatiality. Finally, the literature review concludes with an overview of the consequences of educational mismatch and how to measure those consequences.

Measuring Educational Mismatch:

Educational mismatch and skill information can be captured using objective methods, subjective methods or a combination of both (Flisi et al., 2017). Objective methods, such as normative job analysis or statistical realized matches, utilize information exogenous to the data to categorize the educational requirements for occupations.

A normative job analysis is a formal analysis conducted by a job specialist where the required level of education is determined for each occupational job classification, such as what is done to create the Dictionary of Occupational Titles. Overeducation or educational mismatch is represented by a lower educational requirement for this job than is attained by the individual. Statistical realized matches, on the other hand, aggregates data on workers in a given occupation and determines the required level of education based on the average educational requirement of the workers in that job (Hartog, 2000; Morgado et al., 2016). Subjective methods of measuring overeducation include self-assessment and self-reporting and are solely dependent on worker-provided information. These self-assessments require workers to identify either directly the level of education that they think is necessary for their job or indirectly whether they believe their level of education is suitable to their job.

While less objective than the job analysis or statistical realized matches methods, self-assessment methods do not require the use of third party analysis and can sometimes be better fitted in explaining educational requirements for some occupations that have a high variance in day to day tasks and requirements (Flisi et al., 2017; Hartog, 2000; Morgado et al., 2016). Furthermore, in an extensive cross-country comparison of overeducation measures in European studies, Capsada-Munsech (2019) finds that the worker self-assessment, compared to normative job analysis and realized matches methods, was the only method to consistently and reliably capture overeducation rates across countries and capture the explanatory power of overeducation.

Causes of Educational Mismatch:

There are several key hypotheses explaining the causes of educational mismatch. According to the theory of career mobility, educational mismatch is a short-term phenomenon at the begining of a career, where individuals starting out their career may have a higher likelihood of being overeducated (Sicherman & Galor, 1990). Evaluations of the theory of career mobility are most accurately conducting using time series data, due to the advantage of following an individual through their career path, but can be captured in cross-sectional data using number of years since graduation as a proxy for an individual's experience in their career. There are mixed results on this hypothesis and multiple empirical studies found that the employment mismatch remained persistent years after career start and a lack of evidence of improvement with career transitions (Büchel & Mertens, 2004; P. J. Sloane et al., 1999). The advancement hypothesis, developed by Büchel and Mertens (2004) to explain the persistence of wage penalty of overeducation, suggests that overreduction might be prompted by a lack of opportunities for advancement in their field or place of work.

The heterogeneity hypothesis suggests that the increase in educational attainment and wider availability of college education has resulted in larger variation in ability and skillset of graduates (Chevalier, 2003). In traditional theory, workers are treated as homogenous but more recent theoretical models examining overqualification and overeducation allowed heterogeneity in these areas with endogenous worker skills and job skill requirements (Albrecht & Vroman, 2002; Dolado et al., 2009). Heterogeneity across employers and job applicant characteristics has been shown to impact job matching.

A supply and demand imbalance theory for educational mismatch suggests that there is a mismatch in educational skillset demanded in the labor market, where there are too many college graduates searching for employment in positions with too low a demand for college-graduate skilled labor (Tsang & Levin, 1985; Vedder et al., 2013). Croce and Ghignoni (2012) evaluate the effect of this mismatch on labor market matching in Europe, finding evidence to reject this theory but identify a relationship between regional labor market conditions and overeducation. The policy recommendation from this finding is centered on providing assistance to overeducated workers in labor relocation in addition to supporting the unemployed labor force. The imbalance of supply and demand can be evaluated through a spatial lens, where willingness to relocate, commuting ability, size, and specialization of the labor market may increase the likelihood of match by expanding the demand for labor.

Determinants of Educational Mismatch:

Previous empirical work has identified a strong relationship between regional characteristics and educational mismatch (Abel & Deitz, 2015; Davia et al., 2017; Fedorets et al., 2019), however, the relationship is interlinked with, or reliant on controlling for, other determinants of overeducation such as educational, individual, and employment characteristics. These studies typically focus on regional characteristics such as population size, labor market characteristics, industrial composition, or proximity to metropolitan areas. For example, a region's population size, a proxy for urbanization, might be an important factor affecting a person's labor market match because large cities provide thick labor markets with jobs across the entire spectrum of skills and educational attainment.

Educational characteristics, such as degree attained and field of study, can be a contributor to educational mismatch. A higher degree level, such as a master's degree or PhD relative to a bachelor's degree, has been found to increase likelihood of job match (Robst, 2007). The field of study of an individual impact the likelihood of overeducation due to the relationship between field of study and labor market outcomes (Hansen, 2001; Rossen et al., 2019; van de Werfhorst & Kraaykamp, 2001). Field of studies differ by occupational focus, transitivity of skill to the workplace, and job-specificity (Ortiz &

Kucel, 2008; Reimer et al., 2008). For example, an engineering degree may provide a more direct path and set of skills to employment as an engineer, thus decreasing the likelihood of overeducation. Otiz and Kucel (2008) find that services and human arts fields of studies are most likely to exhibit overeducation, relative to the base category of social sciences, business and law.

Employment characteristics are found in the literature to be impactful on likelihood of educational mismatch. The direct relationship between college major and occupation-educational mismatch identified in the literature also suggests that certain occupations might experience higher overeducation rates than others due to that skill transitivity. Occupations with an excess supply of college-graduated workers have been shown to require higher field-specific skillset to achieve matching (Humburg et al., 2017). Other studies also examined the impact of characteristics, such as phrasing of the job-title, applicant characteristics, such as entrepreneurial skills have on job outcomes and applicant quality in job matching (Abel & Deitz, 2015; Kucel et al., 2016; Marinescu & Wolthoff, 2019). Sector of employment has an impact on overeducation, where public sector employment has a lower risk of overeducation than private sector (Barone & Ortiz Gervasi, 2010; Wolbers, 2003).

As suggested by the heterogeneity hypothesis, variation in individual characteristics, such as skillset and demographics, can be a determinant of educational mismatch. Educational mismatch is not synonymous with a skill mismatch, which is a mismatch between the skills required for a given job rather than a mismatch between the educational credentials, because skill level can fluctuate with built and lost skillsets. Educational mismatch can contribute extensively to skill mismatch (Flisi et al., 2017; Peter J. Sloane, 2014; Wronowska, 2017).

Demographic characteristics, such as marital status and gender are all found to be impactful on educational mismatch. Those who have never been married have been shown to be less likely to be overeducated (Robst, 2008). The socio-economic impacts of overeducation, such as perceived job mobility, job satisfaction, and wages, are shown in some studies to be exacerbated in women, especially if they are caregivers to young children (Castagnetti et al., 2018; Shevchuk et al., 2015).

A spatial theory explaining educational mismatch, known as the theory of differential overqualification, emerged in the work of Frank (1978), theorizing that a family unit's global market is determined by the husband's employment, restricting married women to act as 'tied movers' or 'tied stayers' with employment prospects limited to their local region. Based on the theory of differential overqualification, size of place would have a strong link with overeducation, since smaller labor markets would provide fewer matching opportunities. McGoldrick & Robst (1996) find results disproving this theory using US data. Büchel & Battu (2003) incorporate commuting distance into their analysis, finding that, while married women run a higher likelihood of overeducation in small localities, controlling for commuting ability through the distance of commute shows that both women and men (to a smaller degree) are more likely to be overeducated in small localities.

There are mixed findings on whether women more likely to be overeducated (Battu et al., 2000; McGoldrick & Robst, 1996) or less likely (Castagnetti et al., 2018). Ramos and Sanromá, (2013) find that gender differences are not significant determinants of overeducation, controlling for all other factors. However, there are gender differences in the relationship between field of study and overeducation, where self- selection due to gender norms results in an unequal distribution of males and females in different fields (Attanasio & Kaufmann, 2017; McGoldrick & Robst, 1996; Zhao et al., 2017).

Rossen et al. (2019) find that male graduates in the services, natural sciences, and agriculture fields of study were most likely to be overeducated, relative to the social sciences, journalism and information field of study, whereas those in health and welfare, education, engineering, and arts and humanities were less likely to be overeducated. Due to the systematic differences in educational and occupational decisions, some studies split their sample by gender and run separate models (Di Paolo et al., 2017; Romaní et al., 2016). Tarvid (2015) finds that overeducation varied by industry of employment and that the likelihood of overeducation was systematically different between men and women, when the sample was split into groups. Overeducation was most prevalent in the Finance, Professional/Scientific, and Administrative industries for females and Administrative, Accommodation, and Public Administration industries for males.

When it comes to spatiality and overeducation, two groups of variables are considered: local labor market conditions and degree of spatial flexibility (Romaní et al., 2016). Local labor market conditions, such as urban agglomeration and regional unemployment, and regional industrial composition have been linked with job matching. The higher concentration of human capital that breeds productivity in agglomerated areas increases the likelihood of achieving a job match (Andersson et al., 2007; Buchner & Hoffmann-Rehnitz, 2011; Helsley & Strange, 1990). Abel and Deitz (2015) identify a strong relationship between regional agglomeration and job-matching for college graduates, measuring agglomeration by both population size and employment density.

Croce and Ghignoni (2012) find that fluctuations in labor market conditions, such as economic shocks, exacerbate the likelihood of overeducation. The linkage between unemployment rate and job availability suggests a linkage between regional economic conditions and overeducation likelihood, making it a common spatial determinant of overeducation. Unemployment rate in the region has been found to be positively correlated with overeducation (Romaní et al., 2016).

The degree of spatial flexibility includes variables concerning mobility willingness and ability, such as distance to concentrated labor market areas or access to a vehicle. Commuting ability and willingness, means of transportation, location preferences and migration willingness, and regional job density are also determining factors in the likelihood of a job match (Büchel & van Ham, 2003; Romaní et al., 2016). Romaní et al. (2016) examine the effect of worker willingness to relocate on overeducation, finding a strong negative relationship between willingness to relocate for work and overeducation. Dolton et al. (2001) also find that overeducation decreases with higher mobility.

Consequences of Educational Mismatch

Educational mismatch is indicative of a market failure, as laborers are not utilizing their full credentials in their job (Peter J. Sloane, 2014). Empirical studies have shown educational mismatches to be associated with decreased job satisfaction, career persistent wage penalties, and higher job turnover, (Dolton et al., 2001; Peter J. Sloane, 2014; Verhaest & Omey, 2006). The decreased wellbeing associated has been shown to have even greater effects. Through an investigation of shadow prices and overeducation, Verhaest & Omey (2009) calculate a need up to a 27% wage increase per overeducation year to make up for the psychological costs of overeducation in the first job.

Croce and Ghignoni (2012) identify an inverse relationship between wages and overeducation incidence. Contrary to the Theory of Career Mobility, overeducation is shown to negatively affect long term wage trajectories (Büchel & Mertens, 2004). The wage penalty for educational mismatch is significant at a degree level but exacerbated when measured at a field of study level. Educational mismatch between field of study and education rate has been shown to have detrimental outcomes on wage, especially for fields of study with lower skill to occupation transitivity (Attanasio & Kaufmann, 2017; Clark et al., 2017; Robst, 2008; Zhao et al., 2017). Furthermore, evidence suggests that overeducation may exacerbate the gender wage gap (Salinas-Jiménez et al., 2013).

Most commonly, a probit or logit model is used to measure the incidence of educational mismatch (Abel & Deitz, 2015; Battu et al., 2000; Groot & Maassen van den Brink, 2000) , with a dummy variable for whether a job match was achieved acts as the dependent variable. To measure the wage penalty of educational mismatch a Mincerian wage equation, as per Mincer (1974), is commonly used. The wage equation is specified using ordinary least squares, with natural log of wage as the dependent variable and wage as a function of occupation, industry, and demographic characteristics (Groot & Maassen van den Brink, 2000; Lahiguera & Martínez, 2012; Salinas-Jiménez et al., 2013). The literature is consistent showing that overeducated individuals are subject to have lower wages than those who have an education match (Abel & Deitz, 2015; Clark et al., 2017; Lahiguera & Martínez, 2012).

The Mincerian wage equation has also been applied towards understanding the effect of regional agglomeration on job matching. Abel and Deitz (2015) who calculate an urban wage premium for job matching in US metropolitan areas, find a significant and positive wage premium. Figueiredo et al. (2014) investigate the wage premium in Portuguese labor markets for both urbanization and industrial localization as measures of agglomeration, finding that both industrial clustering and urbanization increases the wage premium.

A disadvantage of using the Mincerian wage equation to measure the wage premium of job matching is the innate endogeneity problem, where variables used to explain overeducation now appear alongside overeducation in the OLS equation (Abel & Deitz, 2015). Furthermore, a heterogeneity problem is recognized in the literature, where variation in skillset is not controlled for in the wage model. Despite the recognized problems with heterogeneity with using the Mincerian wage equation method, McGuinness (2008) finds that overeducation estimates in the literature are statistically significant and relevant through the use of propensity score matching.

Hypotheses

The literature suggests that educational mismatch is a phenomenon with substantial consequences to income and well-being and can, in part, explained by variation in regional agglomeration. This paper investigates the impacts of urbanization as well as occupational and industrial localization on job matching, controlling for the educational, employment, and individual characteristics that effect job matching and degree of spatial mobility. There are several key hypotheses investigated by this paper

Hypothesis 1: Urbanization, as measured by size of place, as measured by county population, increases the likelihood of achieving a degree level job match.

Hypothesis 2: Controlling for industry and occupation type, industrial and occupational localization increase the likelihood of job match.

Next, this paper investigates the wage premium of job matching through an implementation of the Mincerian wage equation to test whether overeducation does impact wages, controlling for spatial, educational, individual, and employment characteristics. This paper also investigates whether urbanization increases wages.

Hypothesis 3: There is a wage premium associated with job matching, controlling for individual, employment, educational, and spatial characteristics

Hypothesis 4: There is an urban wage premium, associated with employment in larger counties

Hypothesis 5: There is a wage premium associated with industrial and occupational localization

Data

A survey is administered to 38,940 University of Maine alumni between January and April of 2020 and an additional 10,000 University of Maine alumni via mail postcard in March 2020. Contact information for the alumni is obtained from the University of Maine Alumni Association. The survey was projected to take 15-20 minutes to complete and offered no incentive, likely decreasing response rates. A significant number of emails were undeliverable, suggesting the emails were not regularly updated. Response rates for the survey are captured in Table 2-1.

Table 2-1: Alumni Survey Response Rates

STATUS	N	PERCENT (ALL)	PERCENT (IN SAMPLE)
EMAIL SAMPLE (N = 38, 924)			
Email Sent	27,592	70.90%	83.60%
Undeliverable	5,921	15.20%	<NA>
Finished Survey	3,791	9.74%	11.5%
Partially Completed Survey	1,223	3.14%	3.71%
Opted Out	397	1.02%	1.20%
MAIL SAMPLE (N = 10,000)			
Postcards Sent	9,501	95.01%	
Finished Survey	437	4.37%	
Partially Completed Survey	62	0.62%	
TOTAL DISTRIBUTION (N = 48,924)			
Total Sent	37,093	75.82%	86.26%
Total Finished	4,448	9.09%	10.34%
Total Partially Completed	1,285	2.63%	2.99%
Total Undeliverable	5,921	12.10%	<NA>

After accounting for the undeliverable emails, the email survey had a 15.21% response rate and the mail survey a 4.99% response rate. The survey questions used in this analysis and their corresponding variables and sample counts are depicted in Table 2-2.

Table 2-2: Survey Questions Used in Study

Question	**Variable**
What year did you graduate from the University of Maine with your {{Most Recent}} Degree?	**nyear** = 2019 - [Year of Graduation]
Which of the following best describes your marital status?	**Married** - dummy variable with answers 1 - 2 as Yes and 3-5 as No.
What is the highest level of education you have completed at any university including the University of Maine?	**HighEd**
Which of the following best describes your major for your {{Most Recent Degree}} from the University of Maine?	University of Maine college grouping **School**
What was your total personal income, before taxes, in 2018? >What percentage of your personal income was wage income?	Log(income * percent wage) = **ln(wage)**
If you currently reside in the United States, what is the zip code of your permanent residence?	Zipcode of residence used to optain values for **lnCountyPop** **Unemp_College_P,** **NAICS.LQ, and SOC.LQ**
Which of the following industries most closely matches the industry of your primary employer?	2-dig NAICS code **Industry** dummy **NAICS. LQ**
Please tell us what occupation best matches your current job title.	Major SOC code **Occupation** dummy **SOC.LQ**
How important to you were the following characteristics when choosing to live {{in/outside}} Maine? (1 Not Important) – (6 Extremely Important)/ NA ➢ Career opportunities ➢ Spouse/partner	Dummies to control for location preference **Spouse** **Career**
Does your current job require a college degree?	**DegMatch**
Is your current job related to your major field of study at the University of Maine?	**majMatch**

Additional information on demographics and spatial characteristics is merged with the survey responses. Data on the **age** and **gender** of survey respondents is obtained from the University of Maine Alumni Association database by matching respondents to their demographic information using their response ID[3]. County-level data on labor market conditions (county population, unemployment rate for college graduates, and employment by major industry and occupation) is obtained from the American Community Survey of the U.S. Census Bureau for each respondent. The county-level data is representative of the respondent's county of residence, where survey respondent provided zip codes are matched to their corresponding counties using the HUD-USPS crosswalk. For zip codes spanning across multiple counties, the counties containing the largest proportion of the zip code are used.

In order to be included in the empirical analysis of a person's degree match and earnings, the following conditions are met:

- Respondents who completed at least one degree from the University of Maine.
- Respondents who are currently employed.
- Respondents who can be matched to their alumni records, allowing us to obtain demographic characteristics.
- Respondents who provided a valid zip code for their residence, allowing for obtaining regional characteristics.

After removing individuals from the sample that did not meet these conditions, the number of observations used in the analysis was 2,531.

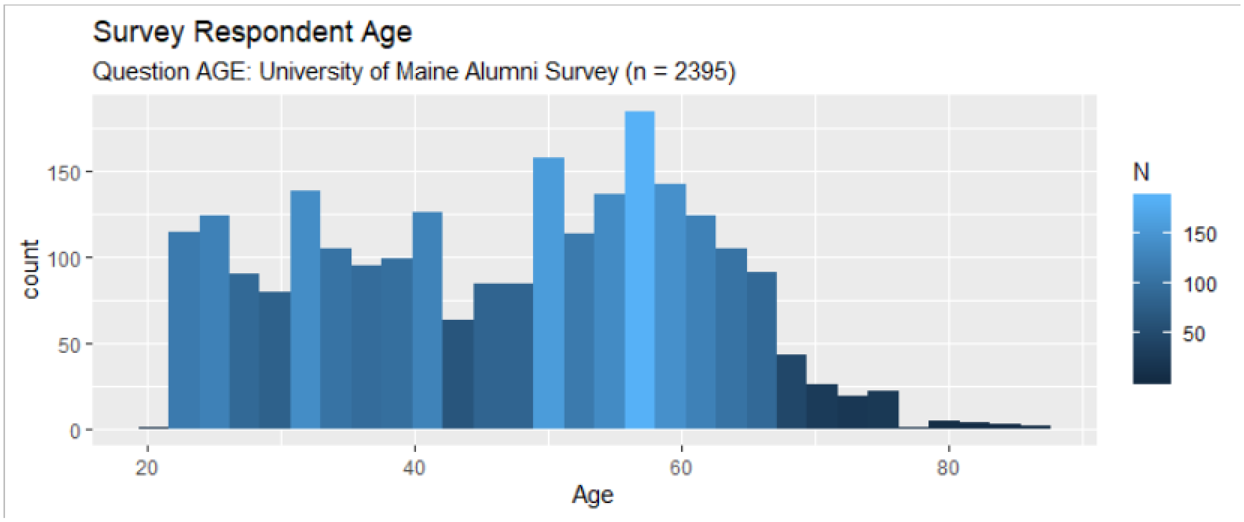
Individual Descriptive Characteristics:

The average age of respondents was 45 (Figure 2-1), which is high but perhaps driven up by the high average age in the state. About half of the respondents were in the State of Maine. The sample is

[3] Survey Respondents were not asked about their age or gender due to the availability of the data in our population dataset as a means of limiting questions asked of respondents.

largely homogeneous in terms of race, with 85% of the respondents having specified that they are white[4].

Figure 2-1: Survey Respondent Age



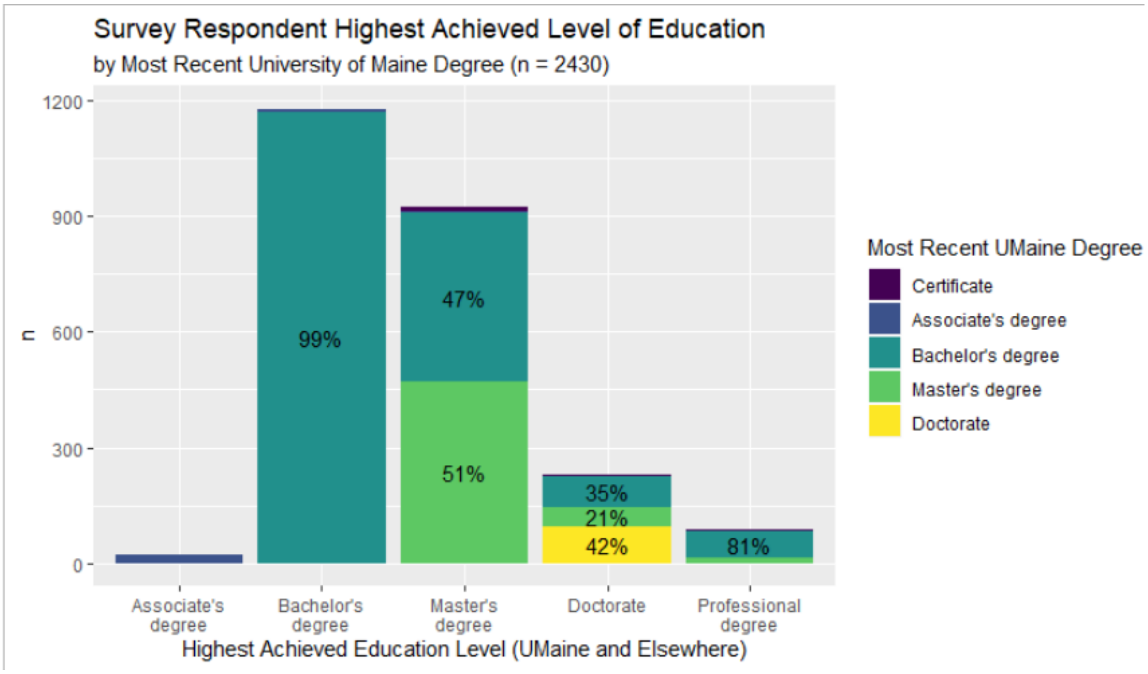
Over 54% of survey respondents are married on their first marriage and 22.8% have never been married. The household income for 42.2% of respondents was over $100,000, with 24% at $100,000 to $149,000. The median individual income was $75,000, with an average of $107,000 driven up by 5 respondents who reported annual incomes of over a million. The average wages calculated by multiplying the income of the respondents by the percentage of income reported to be from wages, were $88,398 with a median of $68,000.

For 72% of respondents, the highest achieved degree level was equivalent to their most recent University of Maine degree, with the proportion of those who received their highest degree level elsewhere increasing with level of education: 99% of bachelor's degree holders and only 42% of

[4] The National Center for Education Statistics reported that 91% of fall enrollment in Maine in postsecondary institutions in 2008 was by those of the white ethnicity ().

doctorate degree holders. Figure 2-2 breaks down the relationship between respondents' most recent University of Maine degree and their highest achieved degree level from any university

Figure 2-2: Survey Respondent Highest Level of Education by Most Recent Umaine Degree

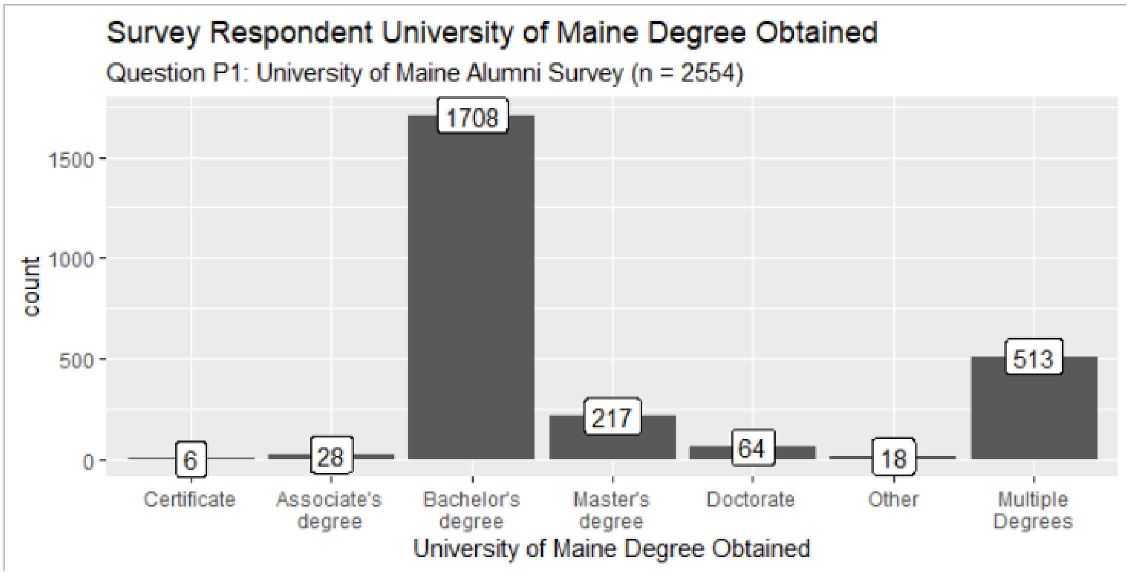


There was a relatively even split of respondents by gender, with a slightly higher response rate of 50.12% for males, however, a t-test identifies systematic differences across responses. Female respondents in this sample, on average, are less likely to be married, potentially because female respondents are also systemically younger than male respondents. There are systematic differences between educational and employment characteristics which will be discussed in the next few sections

Educational Descriptive Characteristics

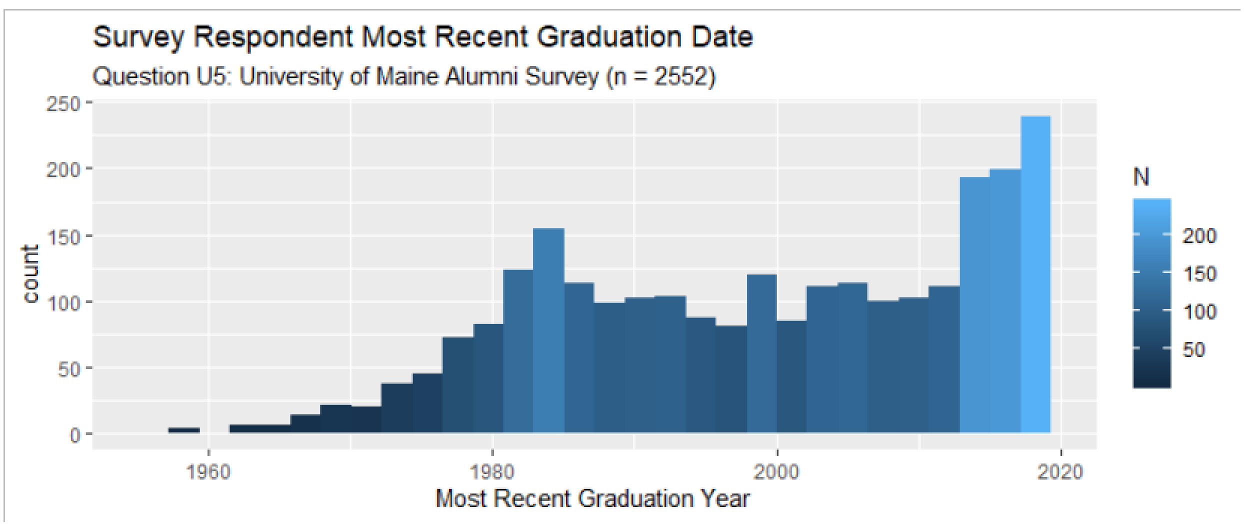
The majority of survey respondents received a Bachelor's degree from the University of Maine, but approximately 20% of respondents achieved more than one degree (Figure 2-3).

Figure 2-3: Respondent University of Maine Degree Obtained



An examination of the most recent graduation year **(**Figure 2-4**)** shows the response data is skewed with more respondents from the 2015-2020 graduation decades.

Figure 2-4: Survey Respondent Degree and Graduation Date



The top 5 majors for each of the five UMaine Colleges from the respondent's most recent University of Maine degree are shown in Table 2-3. The most common majors of graduates across all schools were Business Administration, Education, and Civil Engineering. About 8% of survey respondents achieved degrees with more than one major, the majority of which were combined within a single

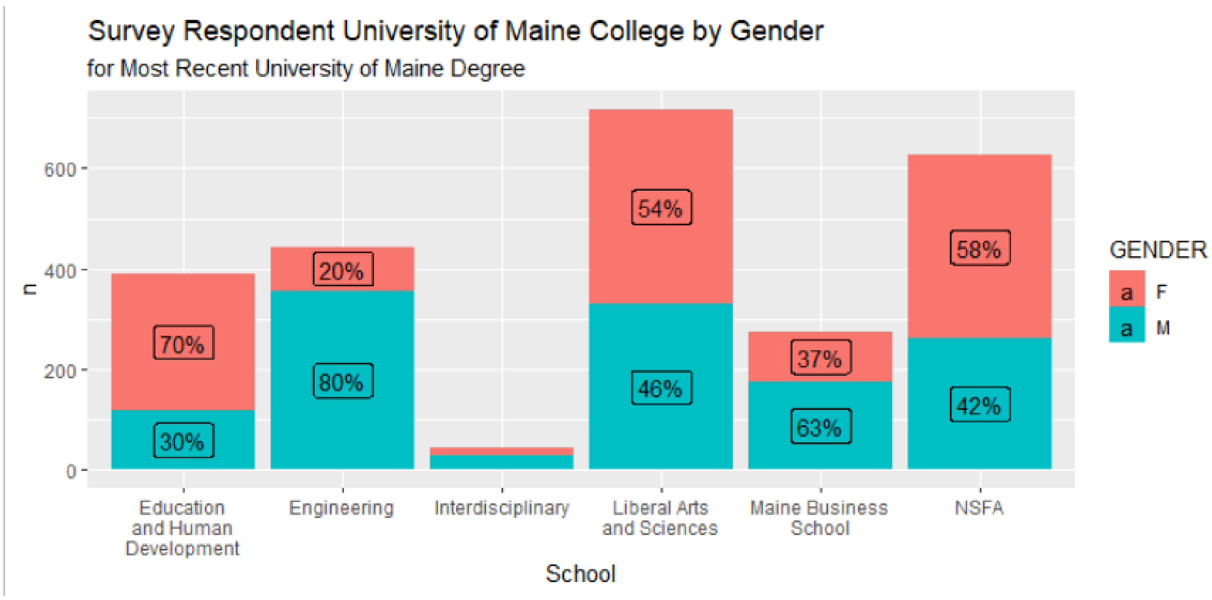
UMaine College. However, 1.68% of respondents achieved interdisciplinary degrees across the University of Maine colleges.

Table 2-3: Top 5 University of Maine Majors of Survey Respondents by School

Major	*N (%)*
Education and Human Development	
Education	104 (3.78%)
Elementary Education	32 (1.16%)
Child Development and Family Relations	31 (1.13%)
Special Education	30 (1.09%)
Counselor Education	27 (0.98%)
Engineering	
Civil Engineering	102 (3.71%)
Chemical Engineering	84 (3.05%)
Mechanical Engineering	61 (2.22%)
Electrical Engineering	45 (1.64%)
Mechanical Engineering Technology	28 (1.02%)
Liberal Arts and Sciences	
English	80 (2.91%)
Political Science	74 (2.69%)
Psychology	54 (1.96%)
Journalism	53 (1.93%)
History	48 (1.74%)
Maine Business School	
Business Administration	132 (4.8%)
Business Management	66 (2.4%)
Finance	25 (0.91%)
Marketing	22 (0.8%)
Accounting	19 (0.69%)
NSFA	
Forestry	47 (1.71%)
Social Work	45 (1.64%)
Economics	40 (1.45%)
Zoology	38 (1.38%)
Nursing	35 (1.27%)

There are systematic differences between genders of respondents and the college of the most recent major (Figure 2-5). The colleges of Education and Human Development, Liberal Arts and Sciences, and NSFA are largely female dominated, while Engineering and the Maine Business School were largely male dominated. Furthermore, female respondents, on average, achieve a higher level of educational attainment and have fewer years since most recent degree.

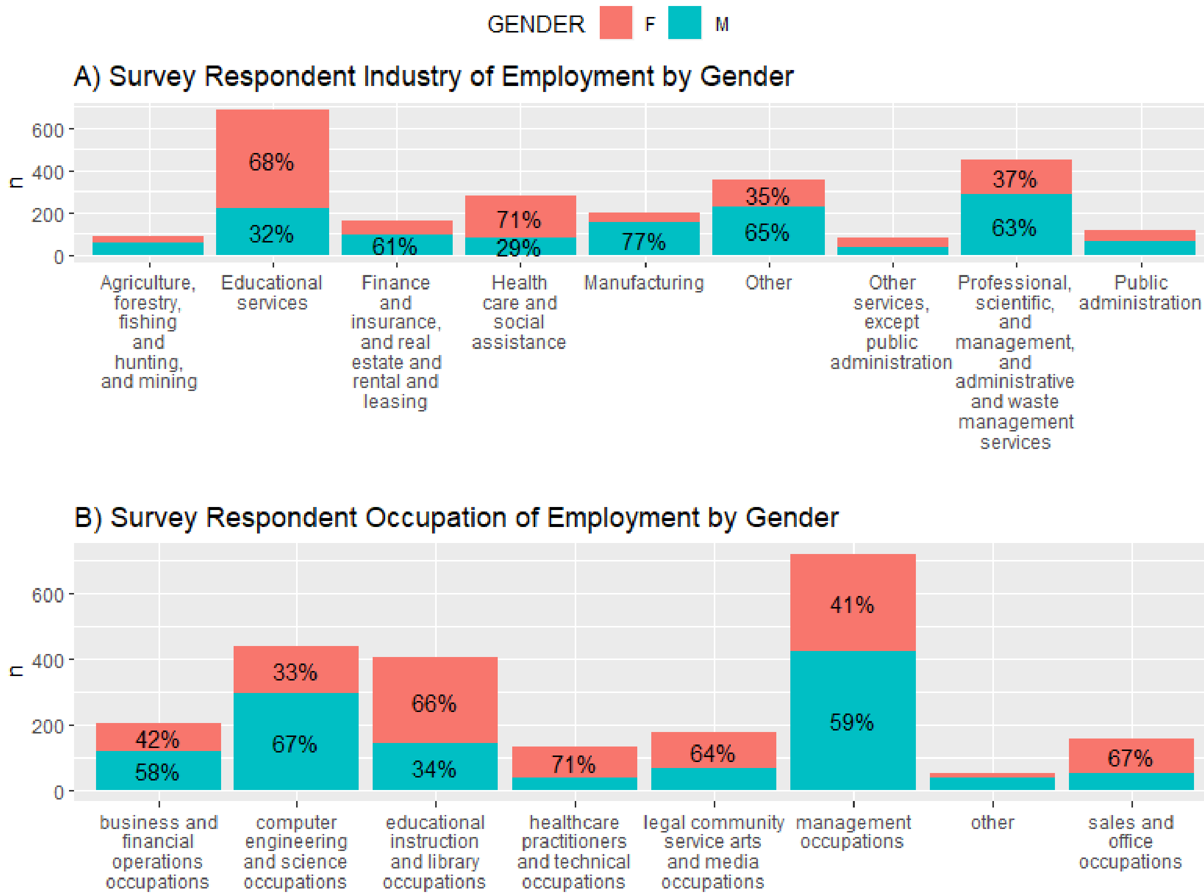
Figure 2-5: Survey Respondent University of Maine College by Gender



Employment Descriptive Characteristics:

The most common occupation major occupational group was management occupations, with 28% of respondents, followed educational instruction and library occupations at 16% of respondents. The most common major industry was Educational Services, at 27%, followed by Professional, Scientific, and Technical Services at 17%. There are systematic differences by gender across major industry and unequal distributions across both occupation and industry **(**Figure 2-6).

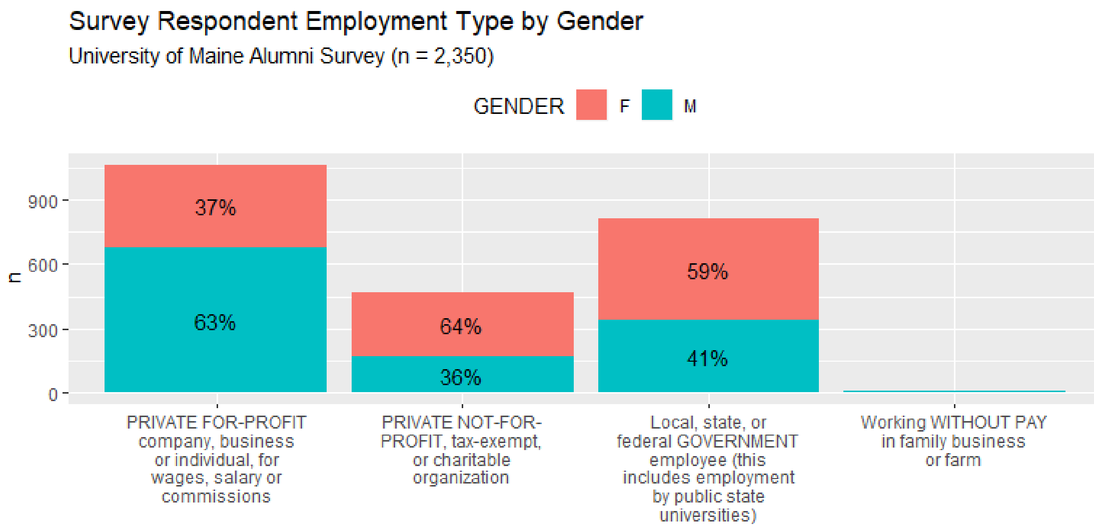
Figure 2-6: Gender Breakdown of major industry and occupation[5]



The majority of respondents are employed in the private sector, with 70% of respondents employed in the private sector working for for-profit companies. 32% of respondents are employed in the public sector. There is a statistically significant difference across genders in employment type. A larger proportion of women are employed in the public sector by non-profit companies in the public sector (Figure 2-7).

[5] Due to the high heterogeneity across occupations for the sample size, the industries are further grouped in a manner adapted from the Census Occupational major groupings.

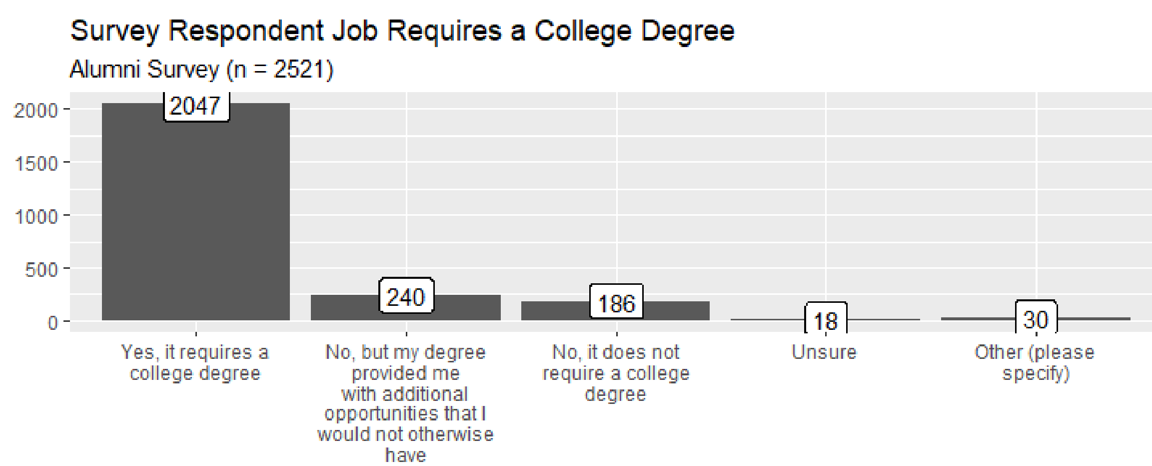
Figure 2-7: Survey Respondent Employment Type by Gender



<u>Methodology:</u>

For the degree level match, variable DegMatch is a self-identified response to whether the job requires a college degree, following the self-assessment method in the literature (Figure 2-8). Respondents who stated that their job required a college degree were counted as job matches whereas respondents who selected either of the No options were counted as a failed match.

Figure 2-8: Responses to Job-Matching variable



To calculate incidence of overeducation, a probit model (Equation (2.1) is constructed to examine to evaluate the degree level match, as is common in the overeducation and job matching literature (Abel & Deitz, 2015; Buchner & Hoffmann-Rehnitz, 2011; Dolton et al., 2001).

$$\Pr(DegMatch = 1) = \varphi\left(\alpha_1 R_j + \alpha_2 X_i + \alpha_3 Emp_i + \alpha_4 Ed_i + \sigma_k\right)$$

$$\begin{aligned} R_j &= regional\ characteristics \\ X_i &= individual\ characteristics \\ Emp_i &= employment\ characteristics \\ Ed_i &= educational\ characteristics \end{aligned} \tag{2.1}$$

To capture the job matching and agglomeration wage premiums, a Mincerian wage equation is utilized (Abel & Deitz, 2015; Figueiredo et al., 2014). The wage equation is calculated using the same explanatory variables as the overeducation incidence model, with the addition of degree match as an additional explanatory variable (Equation (2.3).

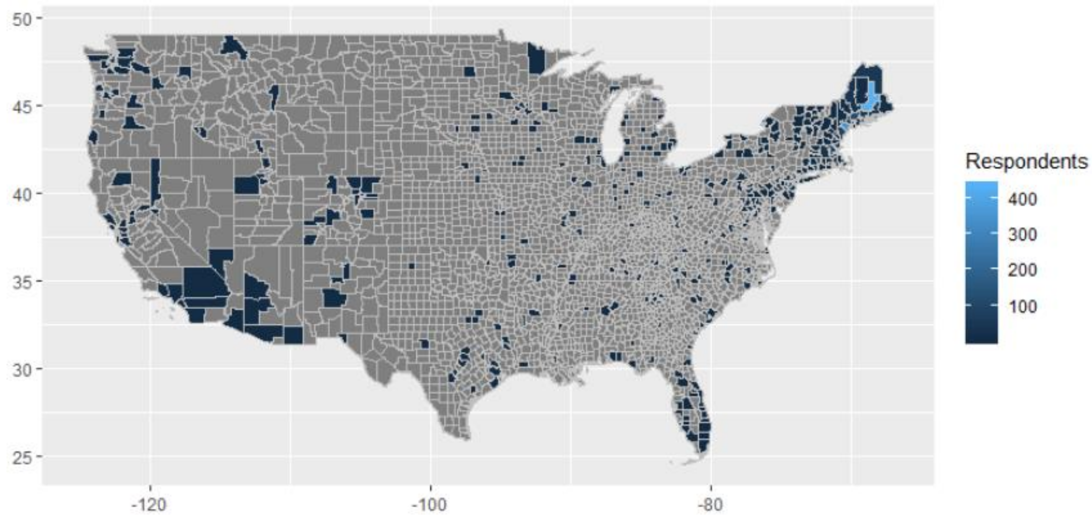
$$\mathrm{lnWage_i} = \alpha_1 R_j + \alpha_2 X_i + \alpha_3 Emp_i + \alpha_4 Ed_i + \alpha_4 DegMatch_i + \sigma_k + \varepsilon_k \tag{2.2}$$

Wages are calculated by multiplying the annual income reported by respondents by the percentage of income allocated to wage income.

Regional Characteristics:

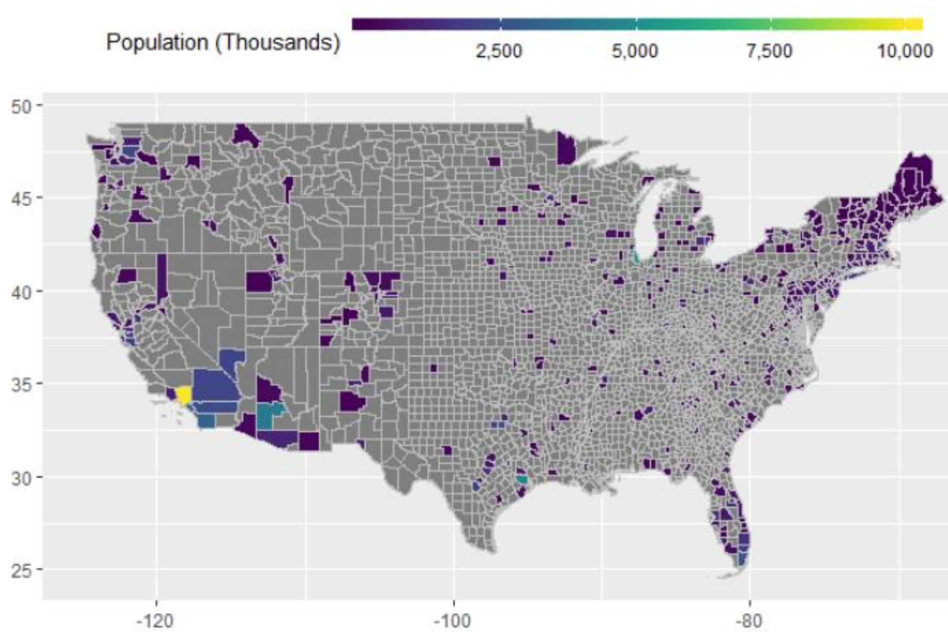
Labor market conditions are captured for the respondent's county of residence, where survey respondent provided zip codes are matching to their corresponding counties using the HUD-USPS crosswalk. For zip codes spanning across multiple counties, the counties containing the largest proportion of the zip code are used. 406 counties, located in 49 of the 50 states are represented, with the highest proportion of respondents located in Maine in Penobscot County (Figure 2-9).

Figure 2-9: Alumni Survey Respondents by County of Residence



The unemployment rate of college-graduates or higher (**unemp_college_p)** is used as a proxy for job availability (Abel & Deitz, 2015; Büchel & van Ham, 2003). The natural log of population (**lnCountyPop**) of the individual's county of residence is used as a measure for regional urbanization (Abel & Deitz, 2015; Figueiredo et al., 2014). County size ranges vastly, with the majority of counties sized less than 2500 (Figure 2-10).

Figure 2-10: Alumni Survey Respondent County of Residence Urbanization



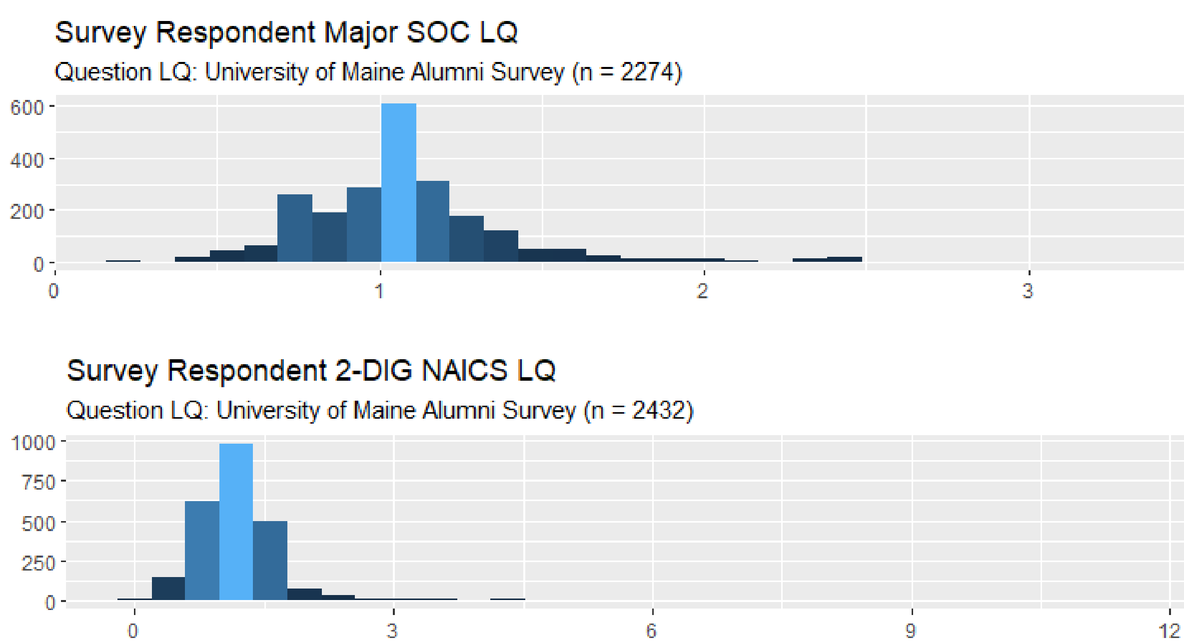
Industrial and occupational location quotients (Equation (2.3) are used to measure industrial and occupational localization as an additional control for local labor market conditions. These act as proxies of regional industrial and occupational clustering and thus economies of scale that may be associated with the industry or occupation of survey respondents (Marshall, 1920).

$$LQ_{ir} = \frac{X_{ir}/X_r}{X_{iN}/X_N}$$

$$\begin{aligned} X_{ir} &= \text{industry/ occupation i's employment in region r} \\ X_r &= \text{total employment in region r} \\ X_{iN} &= \text{industry/occupation i's employment (or establishment count) nationwide} \\ X_N &= \text{total employment nationwide} \end{aligned} \qquad (2.3)$$

County-level location quotients are calculated for the respondent's industry of employment at a 2-digit NAICS code industrial aggregation level and for the individual's occupation at a major SOC group occupational aggregation level. Both the occupational and industrial locational quotients are centered around 1, with some outliers extending past 2 for both occupations and industries (Figure 2-11).

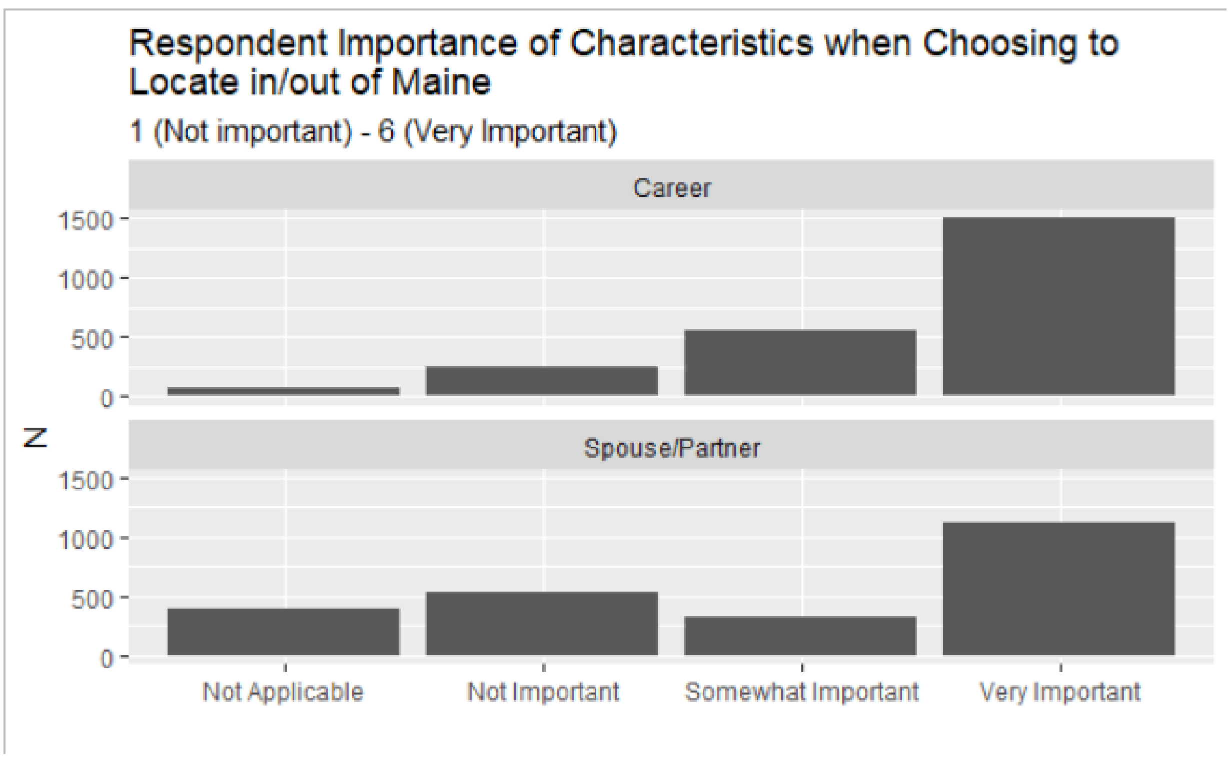
Figure 2-11: Histogram of Location Quotients for major occupation and industry



The degree of spatial flexibility is measured at a state level, using the responses to a question about what characteristics were important to the respondent when choosing to locate either in Maine or out of Maine. Respondents are asked about how important a number of characteristics, including how important career opportunities (**Career**) and their spouse or partner (**Spouse**) were, to their decision to locate either in Maine or outside of Maine. While these are not direct measures, these variables help control for the willingness to relocate by capturing the degree to which the respondent's location decisions are impacted by their career or the location decisions of their spouse or partner, thus acting as a proxy for the theory of differential overqualifications.

The importance of the characteristics is captured on a Likert scale from 1 (not important) to 6 (very important) and include a non-applicable option. Figure 2-12 shows the breakdown of responses for the characteristics of career opportunities (**Career**) and spouse or partner (**Spouse**), where not important captures Likert scale responses 1-2, somewhat important 3-4, and very important 5-6.

Figure 2-12: Degree of Spatial Flexibility of Survey Respondents



For simplicity, the variables Career and Spouse are converted into dummy variables for whether the characteristic was important (Somewhat Important and Very Important groups) or not important (Not Important and Not Applicable groups)

Employment Characteristics Controls

To control for heterogeneity across industry and occupation of employment, aggregated dummy variables for the employment descriptive variables are included. Occupations are aggregated at a major occupational level then further grouped based on Census Occupational groupings. Industry of employment is reported at a 2-digit NAICS code level and aggregated based on Census major industrial groupings. To further preserve explanatory power, occupations and industries with less than 75 responses are grouped into an "other" category.

Educational Characteristic Controls

Number of years since obtaining the most recent University of Maine degree (**nyears**) is used as a proxy for years of experience, showing time since respondents achieved their most recent University of Maine degree. Highest degree attained by the respondent (**HighEd**) is used in place of degree level from the University of Maine degree to cover due to skillset from the additional degree gained.

To account for differences in educational characteristics of respondents, the majors of the respondents most recent degree are grouped into their respective college at the University of Maine (**College**).

Individual Characteristic Controls:

The model controls for commonly used demographic characteristics: namely **gender** of respondent and marital status (**married**). Respondents race is not included due to the data's homogenous nature, with 86% of the respondents specifying that they are white. Number of kids, while shown to be significant towards determining job match, was not important by AIC/BIC criteria and was not included in the analysis. Gender of respondents, found in the data analysis to have significant systematic differences across numerous variables, is included as a dummy variable in a full model but also used to group and run two models to allow for cross comparisons across genders, as is done in the literature. Descriptive statistics for the model variables are captured in Table 2-4 and pairwise correlations in Table 2-5.

Table 2-4: Descriptive Statistics for model variables

Variable	Obs	Mean	Std. Dev.	Min	Max
degMatch	2531	.81	.39	0	1
nyears	2552	20.3	14.63	0	62
Married	2461	1.67	.47	1	2
Gender	2544	1.5	.5	1	2
HighEd2	2469	2.95	1.02	1	5
School2	2504	3.78	1.79	1	6
Career3	2365	1.13	.34	1	2
Spouse2	2354	1.39	.49	1	2
lncountypop	2516	12.31	1.12	7.84	16.12
unemp_college_p	2516	.02	.01	0	.08
Occupation	2274	4.21	2.08	1	8
soclq	2274	1.08	.31	.24	3.31
NAICS_2dig	2432	4.73	2.49	1	9
indlq	2432	1.21	.65	0	11.42

Table 2-5: Pairwise Correlations for Model Variables

Variables	degM~	nyea~	Married	Gender	HighE~	School	Caree~	Spou~	lncoun~	unemp~
nyears	-.09***	1								
Married	.08***	.30***	1							
Gender	-.01	.18***	.14***	1						
HighEd2	.25***	-.01	.09***	-.07***	1					
School2	-.08***	-.01	-.05**	-.05**	-.02	1				
Career3	-.11***	-.01	-.03	-.04**	-.02	.00	1			
Spouse2	-.02	-.04**	-.32***	.04**	-.01	.05**	.02	1		
lncountypop	.09***	.01	-.04**	.04**	.02	.06***	-.11***	.13***	1	
unemp_c~	.00	.05**	-.01	.02	.05**	.05**	-.05**	.12***	.39***	1
Occupation	-.20***	.09***	.02	-.05**	-.04*	.05***	-.01	-.04*	-.04**	.01
soclq	.10***	.00	-.02	-.02	.09***	.05**	-.09***	.13***	.40***	.11***
NAICS_2dig	-.07***	.05***	-.03	.19***	-.09***	.08***	-.08***	.07***	.17***	.05***
indlq	.05**	-.03	-.03	-.01	.01	.06***	-.03	.04**	-.02	.02

Variables	Occ~	soclq	NAICS~
Occupation	1		
soclq	-.12***	1	
NAICS_2dig	-.02	.09***	1
indlq	.02	.24***	-.16***

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

Results and Discussion:

Determinants of Educational Mismatch

The marginal effects of the spatial variables on agglomeration are captured in Table 2-6. A complete table of results is accessible in APPENDIX 2A: COMPLETE MARGINAL EFFECTS OF JOB-MATCHING MODEL

Table 2-6: Probit Model Marginal Effects

	(1) All		(2) Female		(3) Male	
nyears	-0.00	(-1.27)	-0.00	(-1.07)	-0.00	(-0.51)
Married						
> Married	0.02	(0.86)	0.04$^{\cdot}$	(1.47)	-0.01	(-0.46)
Highest Degree						
> Associate's	-0.18	(-1.23)			**-0.39***	**(-1.86)**
> Bachelor's						
> Masters	**0.10*****	**(5.61)**	**0.09*****	**(3.50)**	**0.11*****	**(4.36)**
> Doctorate	**0.14*****	**(4.84)**	**0.13*****	**(3.16)**	**0.15*****	**(4.01)**
> Professional	**0.19*****	**(8.78)**	**0.19*****	**(7.69)**	**0.20*****	**(7.08)**
Career Loc Pref						
> Important	**0.07*****	**(2.84)**	**0.07****	**(2.07)**	0.06$^{\cdot}$	(1.45)
Spouse Loc Pref						
> Important	-0.01	(-0.29)	-0.01	(-0.30)	0.01	(0.47)
lncountypop	**0.03*****	**(4.03)**	0.02	(1.38)	**0.05*****	**(4.12)**
unemp_college_p	**-2.62****	**(-2.16)**	-0.10	(-0.06)	**-4.08****	**(-2.47)**
Employment Type						
> For Profit						
> Non Profit	**0.10*****	**(3.87)**	**0.14*****	**(3.55)**	**0.08****	**(2.03)**
> Govt	**0.09*****	**(3.47)**	**0.09****	**(2.24)**	**0.10*****	**(3.16)**
SOC.LQ	0.04	(1.10)	0.09$^{\cdot}$	(1.60)	0.01	(0.16)
IND.LQ	0.02	(0.97)	-0.02	(-0.72)	**0.04****	**(2.23)**
Observations	1769		841		924	

t statistics in parentheses
Robust standard errors
Hidden controls: UMaine college, gender, marital status, occupation type, occupation industry
$^{\cdot}$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel 1 of Table 2-6 captures the marginal effects of the complete sample, controlling for gender using a dummy variable, whereas Panel 2 and 3 capture the model results when run separately grouped by gender. As expected, achieving a higher overall degree level increases the likelihood of achieving a job match. Compared to a Bachelor's degree, a Master's degree increases the likelihood of a job match by 10%, a Doctorate by 14% and a Professional degree by 19% in the complete model.

Both variables for degree of spatial flexibility tell an interesting story. While not significant, the importance of the partner for location decisions is integral to the model, by AIC/BIC metrics[6]. The dummy for career importance for location preferences is significant at a 1% level in the complete model, yet when split by gender it is only significant for females. This result provides an explanation towards Frank's theory of differential overqualification. Women's job-matching prospects are strongly tied to their degree of spatial flexibility, with career-driven location preferences increasing the likelihood of a job match by 7%.

Urbanization (**lncountypop**) and college graduate unemployment rate (**unemp_college_p**), which both have a significant effect in the complete model, are only significant for males in the gender-split models. These results show that after controlling for degree of spatial flexibility as well as employment and educational characteristics, urbanization and localization are not significant determinants of job matching for females. For male respondents, the likelihood of a job match increases by 5% with a 1% increase in county size and decreases by over 400% when the college graduate unemployment rate increases by a percentage point. Occupational localization is not significant for any group, but industrial localization is significant for the male model.

[6] When evaluating the explanatory power of the model using AIC and BIC criteria, removing the variable capturing the spouse's location preference decreased the model's explanatory power by raising the AIC and BIC.

A possible explanation for the gendered spatial responses stems back to the systematic differences between male and female respondents in educational and employment characteristics. In order to test whether the gendered relationship between urbanization and job matching is a result of females systematically self-selecting into industries for which urbanization does not increase the likelihood of job match, we run the models again, grouped by female-dominated and male-dominated industries. Female-dominated industries are those for which more than 50% of the respondents are female (i.e. Educational Services and Healthcare).

Table 2-7: Marginal Effects for the Spatial Variables with Augmented Industry Groups

	(1) All Ind		(2) Female Ind		(3) Male Ind	
Career Loc Pref						
> Important	**0.07*****	**(2.84)**	0.04	(1.29)	**0.10****	**(2.51)**
> Not Important						
Spouse Loc Pref						
> Important	-0.01	(-0.29)	0.01	(0.33)	-0.00	(-0.04)
> Not Important						
lncountypop	**0.03*****	**(4.03)**	0.01	(0.54)	**0.06*****	**(4.66)**
unemp_colllege_p	**-2.62****	**(-2.16)**	-1.46	(-0.93)	**-3.43***	**(-1.93)**
SOC.LQ	0.04	(1.10)	**0.15****	**(2.49)**	-0.02	(-0.51)
IND.LQ	0.02	(0.97)	-0.01	(-0.39)	**0.04****	**(2.15)**
Observations	1769		708		1060	

t statistics in parentheses
Robust standard errors
Hidden controls: degree attainment, UMaine college, years since graduation, marital status, gender, occupation type, occupation industry
$^{\cdot}$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Marginal effects for the spatial variables in the augmented groups are shown in Table 2-7. The results support the hypothesis that the relationship between urbanization and job matching is tied to industry. For the female-dominated industries, consisting of healthcare and education, urbanization is not a significant determinant of job match nor is the degree of spatial flexibility. However, a one unit increase in occupational localization increases the likelihood of job match by 15%. In the male-dominated industries, which consists of all other industries, urbanization and industrial localization are significant determinants of job matching.

Performing the same test for occupational groupings yields similar results **(**Table 2-8**)**. The female dominated occupations consist of office and sales occupations, healthcare services, and educational services occupations. Urbanization is not a significant determinant of job matching for female dominated occupations but is statistically significant at a 1% level for male-dominated industries. Regional college graduate unemployment rate is small and not significant for female dominated occupations and is significant at a 1% level for male dominated, with a percentage point increase in unemployment resulting in a decrease in job matching likelihood of over 450%. For female dominated occupations specifically, localization has a significant and large effect, with a one unit increase in a 24% increase in job matching likelihood. Career-oriented location importance is significant across all groups.

Table 2-8: Marginal Effects for Spatial Variables with Augmented Occupation Groups

	(1) All Occ		(2) Female Occ		(3) Male Occ	
Career Loc Pref						
> Important	**0.07*****	**(2.84)**	**0.08****	**(2.20)**	**0.07***	**(1.88)**
> Not Important						
Spouse Loc Pref						
> Important	-0.01	(-0.29)	-0.00	(-0.05)	0.00	(0.03)
> Not Important						
lncountypop	**0.03*****	**(4.03)**	0.01	(0.87)	**0.06*****	**(5.57)**
unemp_colllege_p	**-2.62****	**(-2.16)**	0.85	(0.47)	**-4.51*****	**(-2.79)**
SOC.LQ	0.04	(1.10)	**0.24*****	**(2.92)**	-0.02	(-0.56)
IND.LQ	0.02	(0.97)	-0.00	(-0.05)	0.01	(0.61)
Observations	1769		641		1112	

t statistics in parentheses
Robust standard errors
Hidden controls: degree attainment, UMaine college, years since graduation, marital status, gender, occupation type, occupation industry
$^{\cdot}$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Dummy variables for the for the occupational and industry gender-groupings used in the above tests are introduced into the original models in place of the industry and occupation groups to control for the identified link between female-dominated industries and occupations and urbanization. Table 2-9 shows the marginal effects of spatial variables on job matching, with the gender-occupation and gender-industry groups. Working in a male-dominated occupation increases the likelihood of job matching for all groups at a 1% level of significance. Working in a male-dominated industry, on the other hand, decreases the likelihood of job matching for females and in the combined sample. This can likely be attributed to the female-dominated industries of healthcare and education having a high likelihood of job-matching.

Table 2-9: Marginal Effects of Spatial Variables after Controlling for Industry and Occupation Self-selection

		(1) All		(2) Female		(3) Male
Career Loc Pref						
> Important	**0.08*****	**(2.91)**	**0.08****	**(2.19)**	**0.08***	**(1.82)**
> Not Important						
Spouse Loc Pref						
> Important	0.00	(0.13)	-0.00	(-0.08)	0.02	(0.61)
> Not Important						
lncountypop	**0.04*****	**(4.41)**	**0.02***	**(1.76)**	**0.05*****	**(4.31)**
unemp_colllege_p	**-2.43***	**(-1.92)**	-0.75	(-0.45)	**-3.23***	**(-1.78)**
Occupation						
> Female-Dominated						
> Male-Dominated	**0.10*****	**(4.24)**	**0.08*****	**(3.06)**	**0.11*****	**(2.73)**
SOC.LQ	0.06$^{\cdot}$	(1.59)	**0.13****	**(2.14)**	0.02	(0.48)
Industry						
> Female-Dominated						
> Male-Dominated	**-0.07*****	**(-3.02)**	**-0.08****	**(-2.48)**	-0.05$^{\cdot}$	(-1.51)
IND.LQ	0.01	(0.84)	-0.01	(-0.38)	0.03	(1.35)
Observations	1769		841		924	

t statistics in parentheses
Robust standard errors
Hidden controls: Highest Degree, UMaine college, years since Grad, gender (1), marital status, employment type
$^{\cdot}$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

These results are conducive with the above theory of differences in employment characteristics for female-dominated and male-dominated industries effecting the link between gender and urbanization. After controlling for the employment self-selection, urbanization becomes impactful for all categories. Career location preference is significant for the combined group and both genders. Occupational localization is significant only for the female group.

Job Match Wage Premium

To understand the wage implications of the college job-match on wages, a Mincerian model is run, with dependent variable log(wages). Regression results are shown in Table 2-10. For the combined group as well as each gendered model, degree match has a significant and large impact on wages. A degree match increases wages by 40%-44%, depending on gender group, ceteris paribus. Urbanization is significant across all the groups but is largest for females. A 1% increase in county of residence increases wages by 10% for women, at a 1% level of significance. The model does not identify an effect of spatial mobility or localization on wages after controlling for individual, educational, employment, and regional labor market characteristics.

Number of years since school has a positive impact on wages, with a significant yet non-consequential diminishing effect. These findings are in support of the theory of career mobility. Marital status has a positive effect on wages across genders, but the effect is the smallest for women. Increases in degree level also tend to increase wages across all models. Compared to a Bachelor’s degree, a Masters degree increases wages by 12%, a Doctorate degree by 29%, and a Professional degree by 44% for the complete model. The female group, compared to the male group, experiences a smaller wage premium from a masters and professional degree, but a higher premium from a doctorate degree.

Table 2-10: Marginal Effects of Degree Match and Spatial Variables on ln(wages).

	(1) All		(2) Female		(3) Male	
degMatch	**0.43*****	**(5.15)**	**0.44*****	**(5.00)**	**0.40*****	**(3.03)**
NYEARS	**0.06*****	**(11.51)**	**0.07*****	**(8.53)**	**0.06*****	**(8.15)**
NYEARS # NYEARS	**-0.00*****	**(-8.33)**	**-0.00*****	**(-6.71)**	**-0.00*****	**(-5.96)**
Married						
> Not Married						
> Married	**0.22*****	**(5.57)**	**0.14*****	**(2.64)**	**0.28*****	**(4.60)**
Highest Degree						
> Associate's	-0.55$^{\cdot}$	(-1.49)	-0.36	(-1.39)	-0.70	(-1.37)
> Bachelor's						
> Masters	**0.12*****	**(2.99)**	**0.12****	**(2.38)**	**0.14****	**(2.25)**
> Doctorate	**0.29*****	**(4.89)**	**0.39*****	**(3.69)**	**0.21*****	**(2.71)**
> Professional	**0.44*****	**(4.02)**	**0.35*****	**(2.67)**	**0.57*****	**(3.61)**
Career Loc Pref						
> Important	0.03	(0.55)	0.08	(1.19)	-0.05	(-0.61)
> Not Important						
Spouse Loc Pref						
> Important	0.00	(0.10)	0.05	(0.98)	-0.01	(-0.10)
> Not Important						
lncountypop	**0.08*****	**(4.29)**	**0.10*****	**(3.78)**	**0.06****	**(2.49)**
UNEMP_COLLEGE_P	1.93	(0.70)	3.00	(0.81)	1.91	(0.42)
Employment Type						
> For Profit						
> Non Profit	**-0.14****	**(-2.38)**	-0.05	(-0.47)	**-0.22*****	**(-3.36)**
> Govt	-0.10$^{\cdot}$	(-1.54)	0.02	(0.29)	**-0.23****	**(-2.41)**
SOC.LQ	0.09$^{\cdot}$	(1.53)	0.00	(0.00)	0.14$^{\cdot}$	(1.60)
IND.LQ	0.03	(1.09)	0.05	(1.16)	0.03	(0.84)
Constant	8.45***	(37.28)	7.95***	(23.38)	8.56***	(27.54)
Observations	1588		754		834	

t statistics in parentheses
Robust standard errors
Hidden controls: UMaine college, gender. occupation, occupation industry
$^{\cdot}$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Compared to employment in the for-profit sector, employment in the non-profit sector decreases wages by approximately 14% for the complete model and by 22% in the male-only model. Being employed in the public sector decreases wages by 23% in the male-only model. No effect is identified in the female model, perhaps due to the fact that there is a link between job matches and employment type and the majority of women are employed in either the non-profit or public sector jobs.

Limitations:

The dataset used in this study is limited in size and scope to only University of Maine graduates and, therefore, caution must be used when applying conclusions from this research as applicable to the general US population and general college graduate population. The small size of the sample did not allow for regional fixed effects to be included in the model, thus limiting the explanatory power of this model. Furthermore, survey respondents were spatially concentrated in Maine.

Another limiting factor is that the data is cross-sectional and does not have information about the respondents over time. Furthermore, the respondents are asked only about their most recent job, not their first job over college. This is done to reduce the number of questions asked of respondents but significantly limits the research scope because it decreases the useable sample size considerably. Self-employed and retired employees were not asked about overeducation to limit question fatigue, thus further limiting the sample size by 33%.

While significant and interesting, the variables used to proxy degree of spatial flexibility are limited in their explanatory power. More preferable metrics of degree of spatial flexibility include commuting distance, commuting ability, etc. Furthermore, no information is collected on the firm characteristics or reasons for accepting the job, also drivers of overeducation models.

Conclusion:

This paper investigated the effect of regional agglomeration on job matching for University of Maine graduates. The findings in this paper confirm the theory that regional agglomeration is significant in labor-market matching. Interestingly, the findings show that effect of regional agglomeration is highly impacted not only by gender of respondents but by the unequal self-selection of respondents into occupational and industry groupings.

Occupational localization is significant for female-dominated industries (i.e. educational services, and healthcare and social assistance) and female-dominated occupations (educational instruction and library occupations, healthcare practitioners and technical occupations, and sales and office occupations). Industrial localization is significant for male-dominated industries only. After controlling for the industrial specialization urbanization, a significant determinant of job matching for male dominated industries and occupations, is shown to be a determinant for both genders and occupational localization for both females and males. As found in previous literature (Abel & Deitz, 2015; Figueiredo et al., 2014; Freeman, 1976) there is a wage premium associated with job matching and urbanization but the paper does not find a localization wage premium.

With US college debt levels at $1.47 trillion in 2018, understanding the determinants and implications of overeducation is not just interesting; it is critical. College graduates are faced with decisions on where to locate after graduation and awareness of the implications of that decision on their likelihood of overeducation and their expected wages could be beneficial to their long run success. Furthermore, the differences in these implications by gender and gender-industry relationship cannot be ignored.

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APPENDIX 1A: COMPLETE MARGINAL EFFECTS OF BUSINESS EFFECTS FOR BUSINESS STARTUP MODEL

	(1) No Cutoff		(4) 500 Cutoff		(5) 1000 Cutoff	
ln_pop	**0.15*****	**(12.52)**	**0.19*****	**(11.74)**	**0.23*****	**(10.96)**
ed_higher_p	**0.27*****	**(3.65)**	**0.32*****	**(3.27)**	**0.35*****	**(2.96)**
TaxRate	2.41$^{\cdot}$	(1.48)	**3.66***	**(1.72)**	3.91$^{\cdot}$	(1.55)
govspending_pp	-0.00	(-1.09)	-0.00	(-0.26)	-0.00	(-0.35)
distMun	0.00	(0.05)	-0.00	(-0.21)	0.00	(0.07)
County						
> Androscoggin						
> Aroostook	0.03	(0.50)	0.05	(0.60)	0.03	(0.32)
> Cumberland	**0.05***	**(1.78)**	0.06$^{\cdot}$	(1.64)	**0.07***	**(1.71)**
> Franklin	**0.07***	**(1.81)**	**0.09***	**(1.90)**	0.07	(1.19)
> Hancock	0.00	(0.03)	0.01	(0.22)	0.01	(0.18)
> Kennebec	0.02	(0.51)	0.04	(0.65)	0.04	(0.52)
> Knox	0.03	(0.74)	0.04	(0.81)	0.07	(0.99)
> Lincoln	0.05	(1.27)	0.06	(1.16)	0.08	(1.16)
> Oxford	0.00	(0.05)	0.01	(0.19)	0.01	(0.32)
> Penobscot	-0.00	(-0.01)	-0.00	(-0.11)	0.00	(0.02)
> Piscataquis	0.02	(0.41)	0.02	(0.39)	0.05	(0.60)
> Sagadahoc	0.05	(1.03)	0.06	(0.97)	0.07	(0.97)
> Somerset	0.00	(0.11)	0.00	(0.04)	-0.00	(-0.00)
> Waldo	**0.07***	**(1.79)**	**0.09***	**(1.79)**	0.11$^{\cdot}$	(1.60)
> Washington	0.03	(0.58)	0.07	(0.97)	0.07	(0.78)
> York	0.06*	(1.95)	0.08**	(2.09)	**0.09****	**(2.05)**
Industrial Group						
> Agriculture, Aqua ~						
> Alternative Energy ~	-511.41	(-0.27)	-5.95e+06	(-0.21)	-2.51	(-0.73)
> Biopharmaceuticals	1.79e+10	(0.07)	1.61e+16	(0.05)	61686.32	(0.10)
> Boatbuilding and ~	-511.44	(-0.27)	-5.95e+06	(-0.21)	-2.56	(-0.75)
> Defense	8.21e+21	(0.06)	6.36e+20	(0.06)	434.45	(0.20)
> Electronics and ~	8.98e+17	(0.08)	1.15e+45	(0.05)	5.88e+09	(0.17)
> Engineering and ~	2.86e+19	(0.07)	2.78e+65	(0.02)	2.18e+22	(0.05)
> Environmental Serv~	33158.29	(0.04)	5.12e+06	(0.01)	-2.52	(-0.74)
> Finance and Business ~	8.9e+210	(.)	2.9e+226	(.)	4.07e+60	(0.02)
> Forestry-Related ~	10579.73	(0.21)	7.71e+24	(0.07)	4.34e+08	(0.12)
> Information Tech ~	7.69e+70	(0.02)	5.2e+124	(0.01)	1.36e+38	(0.03)
> Materials for Text~	2.63e+50	(0.02)	9.24e+47	(0.02)	1.48e+18	(0.06)
> Medical Devices	2.81e+18	(0.07)	6.57e+17	(0.08)	-2.57	(-0.75)
LQ	**0.05*****	**(4.86)**	**0.08*****	**(3.97)**	**0.09*****	**(3.79)**
Observations	6006		4589		3692	

t statistics in parentheses
Robust standard errors
$^{\cdot}$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

APPENDIX 2A: COMPLETE MARGINAL EFFECTS OF JOB-MATCHING MODEL

	(1) All		(2) Female		(3) Male	
NYEARS	-0.00	(-1.27)	-0.00	(-1.07)	-0.00	(-0.51)
Marital Status						
> Married	0.02	(0.86)	0.04$^{\cdot}$	(1.47)	-0.01	(-0.46)
Highest Degree						
> Associate's	-0.18	(-1.23)	0.00	(.)	**-0.39***	**(-1.86)**
> Doctorate	**0.14*****	**(4.84)**	**0.13*****	**(3.16)**	**0.15*****	**(4.01)**
> Masters	**0.10*****	**(5.61)**	**0.09*****	**(3.50)**	**0.11*****	**(4.36)**
> Professional	**0.19*****	**(8.78)**	**0.19*****	**(7.69)**	**0.20*****	**(7.08)**
UM College						
> Ed and Human Dev	0.03	(1.32)	0.02	(0.82)	0.04	(1.02)
> Engineering	0.03	(1.20)	**0.07***	**(1.80)**	0.03	(1.07)
> Interdisc	-0.05	(-0.71)	-0.03	(-0.32)	-0.07	(-0.68)
> Business	-0.04$^{\cdot}$	(-1.50)	-0.03	(-0.59)	-0.05	(-1.23)
> NSFA	-0.01	(-0.52)	-0.04	(-1.28)	0.01	(0.36)
Career Loc Pref						
> Important	**0.07*****	**(2.84)**	**0.07****	**(2.07)**	0.06$^{\cdot}$	(1.45)
Spouse Loc Pref						
> Important	-0.01	(-0.29)	-0.01	(-0.30)	0.01	(0.47)
lncountypop	**0.03*****	**(4.03)**	0.02	(1.38)	**0.05*****	**(4.12)**
UNEMP_COLLEGE_P	**-2.62****	**(-2.16)**	-0.10	(-0.06)	**-4.08****	**(-2.47)**
Employment Type						
> Non Profit	**0.10*****	**(3.87)**	**0.14*****	**(3.55)**	**0.08****	**(2.03)**
> Govt	**0.09*****	**(3.47)**	**0.09****	**(2.24)**	**0.10*****	**(3.16)**
Occupation						
> Business Fin ~.	**0.30*****	**(6.47)**	**0.30*****	**(5.01)**	**0.27*****	**(3.45)**
> Engineer and Sci~	**0.32*****	**(6.85)**	**0.29*****	**(4.42)**	**0.32*****	**(4.11)**
> Educ and Lib	**0.31*****	**(6.15)**	**0.29*****	**(4.86)**	**0.33*****	**(3.84)**
> Healthcare~	**0.22*****	**(3.48)**	**0.29*****	**(4.18)**	**0.04**	**(0.28)**
> Legal, Community~	**0.28*****	**(5.47)**	**0.30*****	**(4.96)**	**0.24*****	**(2.70)**
> Management	**0.29*****	**(6.55)**	**0.30*****	**(5.56)**	**0.27*****	**(3.48)**
> Other	-0.15*	(-1.70)	-0.19	(-1.40)	-0.14	(-1.15)
SOC.LQ	0.04	(1.10)	0.09$^{\cdot}$	(1.60)	0.01	(0.16)
Industry						
> Agr. forresty~	**0.15*****	**(3.04)**	**0.20*****	**(3.54)**	0.08	(1.02)
> Educ services	**0.10****	**(2.39)**	**0.09***	**(1.71)**	0.07	(1.11)
> Finance and ~	0.05	(1.33)	-0.04	(-0.56)	**0.09****	**(2.01)**
> Healthcare ~	**0.10****	**(2.44)**	0.11*	(1.91)	0.07	(1.15)
> Manufacturing	**0.16*****	**(5.18)**	**0.12***	**(1.95)**	**0.17*****	**(4.86)**
> Other services	0.02	(0.33)	0.01	(0.15)	0.04	(0.45)
> Prof scient~	**0.16*****	**(5.51)**	**0.16*****	**(3.27)**	**0.16*****	**(4.53)**
> Public admin	0.04	(0.70)	0.05	(0.66)	0.03	(0.38)
IND.LQ	0.02	(0.97)	-0.02	(-0.72)	**0.04****	**(2.23)**
Observations	1769		841		924	

t statistics in parentheses
$^{\cdot}$ $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

BIOGRAPHY OF THE AUTHOR

Mariya Pominova was born in Donetsk, Ukraine but was raised in the Greater Boston Area after immigrating to the United States in 2002. She received her Bachelor of Science in Economics from the University of Maine in 2018 and continued on with her Masters immediately after. Her research interests in the field have been in macroeconomics, namely the impact of labor market fluctuations have on regional economic conditions and its policy implications. Mariya is a candidate for a Master of Science degree in Economics from the University of Maine in May 2020. After graduation, she will be continuing her work in macroeconomics at the Federal Reserve Board in Washington DC. She is a candidate for the Master of Science degree in Economics from the University of Maine in May 2020.