Cycling to Work: Is Geography Destiny?[1]

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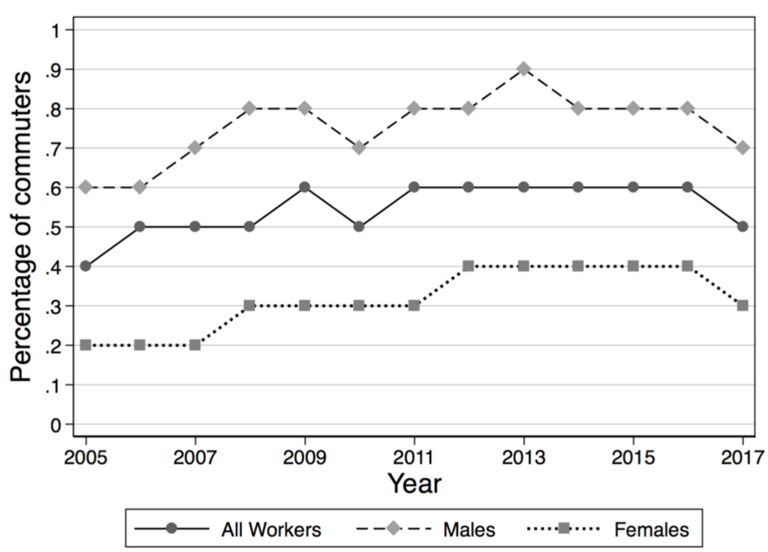
1 Introduction

Cycling has become a pillar of urban transportation planning. Promoting cycling as a form of commuting may benefit the environment, improve public health and lead to a reduction in commuting costs. In 2017, only half of one percent of US workers commuted by bicycle (ACS, 2017), with the share staying relatively stable in recent years (Figure 1). The share of workers who cycle across neighbourhoods and across cities displays considerable heterogeneity. This study will test whether the choice to cycle is substantially determined by local geography, particularly climate and topography. If cycling correlates strongly with geographic conditions, it may be difficult for policy to shift workers to cycling in areas that lack suitable geography.

In recent years, the US has invested substantially in cycling infrastructure. For example, between 2009 and 2015 the US Department of Transportation's TIGER block grant program provided $227 million in funding to projects that were primarily designed to improve cycling infrastructure (US DOT, 2019). Significant funding has also been allocated from other federal programs such as the Congestion Mitigation and Air Quality Improvement Program and from municipal budgets. Such investments suggest a need to evaluate whether cycling is viable in all types of cities.

Figure 1: Share of US Commuters Who Cycle



There is sparse prior research on what geographic conditions causes workers to choose cycling as a mode of commuting. Heinen et al. (2010) provided a thorough overview of the existing literature regarding the determinants of bicycle commuting. The paper offers a summary of past works attempting to determine what causes a commuter to cycle. The environmental determinants of cycling are also considered in Saelens et al. (2003).

Across cities, poor weather and steep hills have been identified as deterrents to cycling. A common finding in the literature is that hilly terrain creates a disincentive to cycle (Parkin et al., 2008; Rietveld and Daniel,

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2004; Rodriguez and Joo, 2004). Rietveld and Daniel (2004) estimated what characteristics correlate with cycling differences across Dutch cities and found the presence of hilly terrain to be among the most important, with hillier cities having lower rates of cycling. I find hillier cities in the US have higher cycling rates, on average. The estimate in Rietveld and Daniel (2004) may have been hindered by the flat topography of the Netherlands leading to almost no slope variation in all but a few Dutch cities. Relatively little research has been done on the relationship between climate and the propensity to cycle. Dill and Carr (2003) note that several US cities with high annual rainfall also have high rates of cycling, suggesting rainfall is not an important factor. Stinson and Bhat (2004) reports lower rates of cycling in the winter, particularly in parts of the US with more extreme seasonal variation in climate.

Considering heterogeneity in cycling choice within cities, the most commonly cited source of variation is distance to work, with cycling more common for shorter routes (Cervero, 1996). The presence of infrastructure such as bike lanes has also been found to be important (Hunt and Abraham, 2007). Bicycle amenities at the workplace such as bicycle parking facilities, locker rooms and showers are sometimes found to be important (Abraham et al., 2002) and in other studies are not (Stinson and Bhat, 2004). This study will focus on the role of inalterable geographic conditions rather than infrastructure and policy variables.

By combining data on 85 million commutes with detailed elevation and climate data, this paper provides novel estimates on the role of geography in determining cycling rates across the US. Section 2 will provide details on data. Section 3 analyses the role of geography in differences in cycling rates across US metros. Section 4 investigates heterogeneity at the neighbourhood level and Section 5 concludes.

2 Data

I combine data from three unique sources (1) the Census Transportation Planning Products (CTPP) 2006-2010 commuting and workplace data set (2) detailed elevation data from the US Geological Survey (USGS) and (3) climate data from the National Oceanic and Atmospheric Administration (NOAA).

The CTPP commuting and workplace data will provide detailed information on commuting habits across the US. The data includes linked data on the home and work locations of workers in the US. Home and work locations are aggregated to the census tract. The CTPP approximates the distribution of the entire US workforce, resulting in a data set representing 85 million commutes. The commuting mode of each observation can be recovered from the data.

In order to conduct analysis on the role of hills in the decision to cycle I construct a detailed data set of elevation points for the US. The USGS provides a web service that returns the elevation of any latitude and longitude coordinates for the US. I first generate a list of every census tract in the US, and calculate the geographic center of each tract. I then use the USGS service to determine the elevation of every census tract. The rich data set allows me to calculate the elevation change faced for any commute between different census tracts.

For metropolitan level analysis I use every metropolitan Core Based Statistical Area (CBSA) in the US, according to 2013 CBSA definitions from the US Office of Management and Budget. I construct a measure of "hilliness" for each metro. I first rank all homes within a metro by their elevation. I then calculate the elevation difference between the 75^{th} percentile and 25^{th} percentile home. This measure can differentiate between metropolitan areas built on significant slopes and those that are relatively flat.

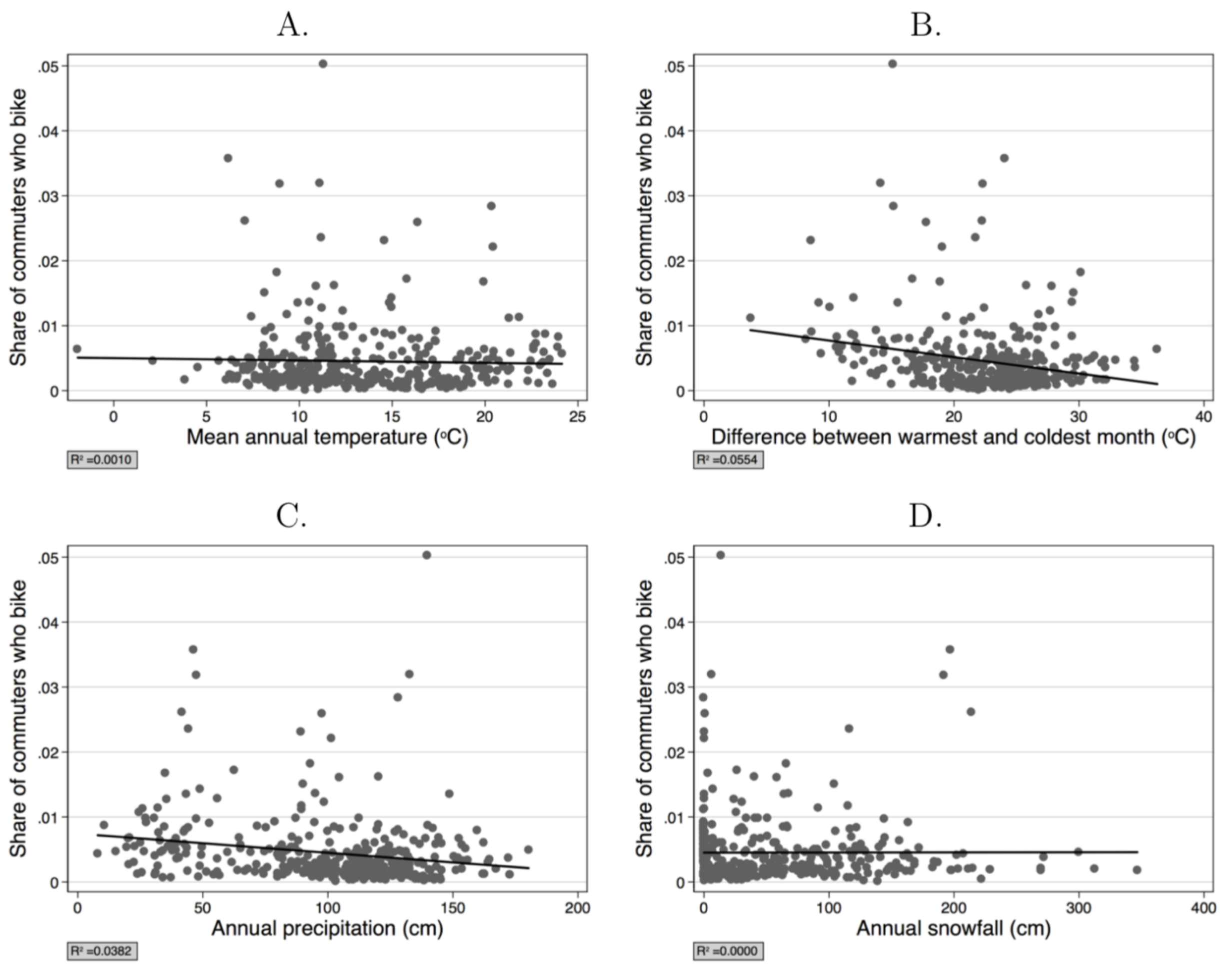
Finally, I estimate the role of climate in determining differences in rates of cycling across metropolitan areas. I use averaged climate conditions estimated by NOAA's 1981-2010 Climate Normals data products. The data set contains "normal" temperature and precipitation conditions across approximately 10,000 weather stations in the US. To calculate metro conditions, I take the average condition across all weather stations that are within the boundaries of a given metro.

3 Geographic Endowment as a Predictor Across Metros

Cycling can potentially be unpleasant in conditions of rain, snow or extreme temperatures. Steep terrain might also act as a deterrent to cycling. I test for a correlation between geographic differences across US metropolitan areas and the prevalence of commuting by bicycle.

Figure 2A displays the correlation between bicycle commuting and mean annual temperature. The figure demonstrates there is essentially no relationship between these two variables. While mean annual temperature in US metros ranges from -2ºC (Fairbanks, AK) to 24ºC (Miami, FL), there is no significant relationship between temperature and the prevalence of bicycle commuting. Table 1, column 1 shows the results of a bivariate regression of the share of commuters who bike and the metropolitan area's average temperature, confirming there is no relationship.

Figure 2: Correlation Between Climate and Bicycle Commuting



Each dot corresponds to a metropolitan area. Lines are unweighted linear best fit lines.

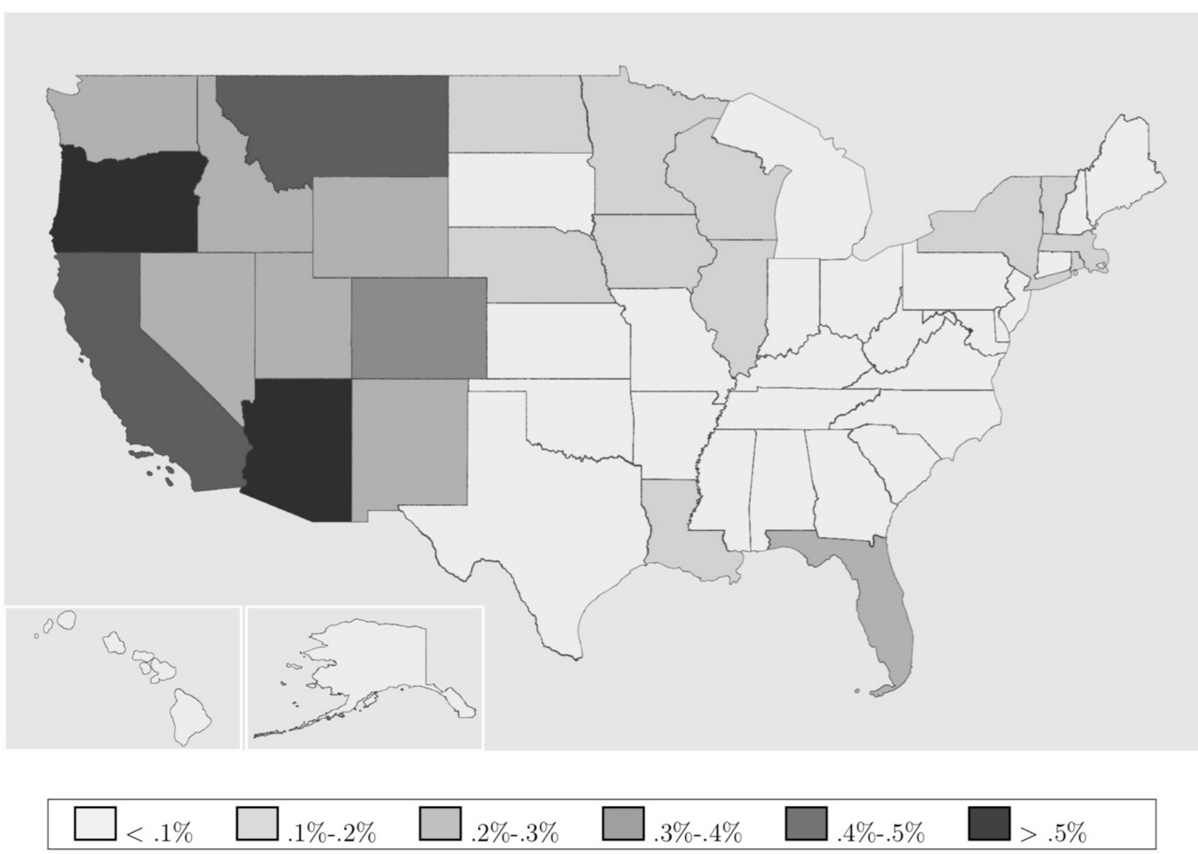
Table 1: Predicting the Share of Metro Workers Commuting by Bycicle

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Average Temperature (°C)	-.004						-.054**	-.054**	-.040*
	(.006)						(.019)	(.019)	(.018)
Temperature Variation (°C)		-.025**					-.062**	-.062**	-.046**
		(.006)					(.013)	(.013)	(.012)
Precipitation (cm)			-.003**				-.003**	-.003**	-.002**
			(.001)				(.001)	(.001)	(.001)
Snow (cm)				.00002			-.001	-.001	-.001
				(.0005)			(.001)	(.001)	(.001)
Elevation span (m)					.001**			.0001	.0003
					(.0006)			(.0005)	(.0005)
Trump vote 2016 (%)						-1.792**			-1.368**
						(.280)			(.242)
Constant	.501**	1.026**	.743**	.450**	.381**	1.388**	2.925**	2.925**	2.999**
	(.092)	(.155)	(.089)	(.041)	(.037)	(.168)	(.542)	(.558)	(.546)
N	364	364	364	364	364	364	364	364	364
R^2	.001	.055	.038	.000	.029	.177	.192	.192	.282

Significance levels: $*$: 5% $**$: 1%. Robust standard errors in parenthesis.

While average temperature does not seem to affect the prevalence of cycling, annual temperature variation does appear important. Figure 2B displays the correlation between cycling and the difference in temperature between the warmest and coldest months of the year. The figure indicates that areas with more extreme annual swings in temperature have lower rates of cycling. Table 1, column 2 estimates that every 10ºC of

Figure 3: Share of Commuters Who Cycle to Work



annual temperature variation reduces the rate of bicycle commuting by 0.25 percentage points, with the average metro having a cycling rate of 0.45%. Annual temperature variation explains 6% of the variation in cycling across metros. Cycling is likely more difficult in rain and snow conditions. Figure 2C and D chart the correlation of bicycle commuting with overall precipitation and snow respectively. Metros with high annual precipitation show lower levels of cycling. Table 1 shows that this relationship is statistically significant. However, variation in annual rainfall only explains only 4% of the variation in cycling across metros. I find no correlative relationship between annual snowfall and cycling.

Table 2: Large metropolitan areas (>1,000,000), bicycle commuting mode share

Rank*	CBSA name	Bicycle Commuting Mode Share
12	Sacramento, CA	1.72%
17	San Jose, CA	1.43%
21	San Francisco, CA	1.29%
26	Phoenix, AZ	1.13%
51	Portland, OR	0.80%
⋮	⋮	⋮
311	Nashville, TN	0.11%
318	Atlanta, GA	0.10%
323	Kansas City, MO	0.09%
339	Birmingham, AL	0.07%
344	Memphis, TN	0.06%

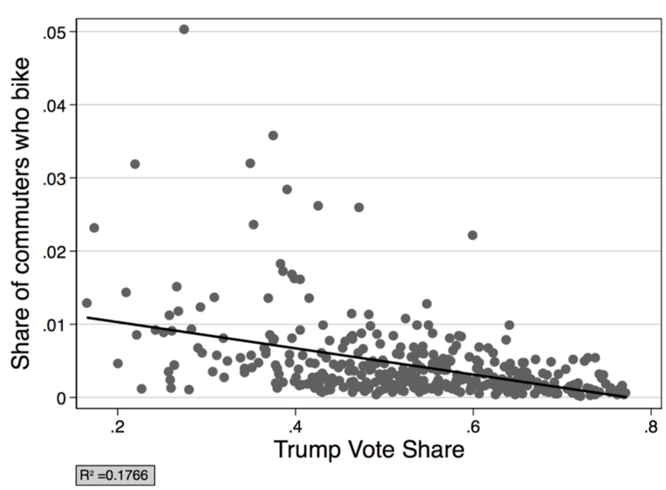
*Rank indicates the CBSA's bicycle commuter share ranking amongst the full set of 353 CBSAs for which data is available.

Taken together in a regression, average temperature, temperature variation, precipitation, and snowfall explain 19% of the variation in metro's percentage of workers commuting by bicycle. Metros with low annual temperature variation, and low rainfall have higher rates of cycling. While the effect of climate on metro cycling rates are statistically significant, they fail to explain a large majority of the cross metropolitan variation.

Metros with flatter topography may be better suited to cycling. I contrast metros with significant variation in elevation to those that are flat, by using the hilliness metric described in the previous section. A bivariate regression of cycling rate against hilliness reveals that metros constructed on hills actually have higher rates of cycling, on average (Table 1, column 5). The metric only explains 3% of the variation across metros. Once climate is controlled for, the effect of hilliness is found to be zero (Table 1, column 8).

Geographic endowment explains only a small amount of the heterogeneity in cycling rates across metros. Figure 3 shows the variation in bicycle commuting across US states. There is a clear relationship with higher rates of bicycle uptake in the western states. Oregon has the highest rate of bicycle commuting in the US, with 1.20% of commuters choosing to cycle. The state with the lowest rate is Alabama, where only 0.08% of commuters cycle. Table 2 shows the five large (population over one million) metropolitan areas with the highest rates of commuting by bicycle. Three of the top five are located in California. Of all metropolitan areas, the metro with the highest rate of commuting by bicycle is Corvallis, Oregon, where 5.0% of commuters choose to bike. The large metros with the lowest

Figure 4: Relationship between bicycle commute share Trump vote share



uptake of cycling are all in the South, consistent with Figure 3. In the Memphis, Tennessee metro only one out of every 1,600 commuters chooses cycling.

The results of Figure 3 and Table 2 suggest that there may be a cultural dimension to cycling mode share. Figure 4 graphs the correlation between bicycle commuting share and the share of a metro's population that voted for Donald Trump for president in 2016. I find a highly statistically significant relationship, with metros that voted for Trump having very low rates of bicycle commuting. Table 1, column 6 confirms this relationship. The vote share explains 18% of the raw variation in cycling share, essentially the same explanatory power as all geographic variables combined. When included in a regression that controls for climate and topography (Table 1, column 9) I still find a strong relationship between vote share of cycling. In the controlled regression, a 10% increase in vote share relates to a .14 percentage point reduction in bicycle commute mode share.

4 Geographic Endowment as a Predictor Within Metros

In this section I test how the elevation gradients faced by commuters affects the probability of a worker commuting by bicycle. If workers are unwilling to commute along routes that include a steep elevation change, cycling infrastructure along these routes may do little to change behaviour. I ignore the role of climate in this section; assuming it to be relatively uniform within the boundaries of each metro. This section will make use of micro data on individual commutes.

In terms of the geography of a route that may affect the choice to cycle, the distance between home and work is likely to be important, with shorter commutes being more suited to cycling. The presence of hills may also be a deterrent. I capture the presence of hills by taking the difference between the elevation of the home location and the work location. This method is meant to capture meaningful variation in hilliness, but is unable to differentiate flat commutes from commutes that have hills, but happen to terminate at the same elevation they began. I also test for the possibility that uphill commuting may be more affecting on the morning commute rather than the commute home.

Regressing mode choice on route characteristics may encounter omitted variable bias. Workers in particular neighbourhoods may be more or less likely to commute by bicycle. For example, consider a city where jobs and low income housing are located at low elevations, while high income housing is located at higher elevations. If cycling is correlated with income, regressions may suggest strong relationships between cycling and elevation characteristics even if elevation changes are not causally impacting choices. I overcome this type of bias by including regression fixed effects for the worker's home census tract and work census tract. Fixed effects fully remove any heterogeneity in cycling commute likelihood that is correlated with the home neighbourhood or work neighbourhood of a commuter. Regression results therefore capture the role of hills on cycling mode choice for hypothetical workers that face identical conditions in their home and work neighbourhoods.

I execute a linear regression model as represented in equation 1, where B is a dummy variable that takes a value of one if the commuter cycles, D is the linear distance between home and work, E is the absolute value of the elevation change between the home and work location, δ is a dummy variable that takes a value of one if the worker's home location is at a higher elevation than the work location, ϕ is a fixed effect for home tract and ψ is a fixed effect for work tract. The regression is executed on CTPP commuting data that covers 85 million commuters.

Equation 1

$$B_i = \beta_0 + \beta_1 D_i + \beta_2 E_i + \beta_3 \delta_i + \phi_{h(i)} + \psi_{w(i)} + \varepsilon_i$$

Results of the micro level analysis are displayed in Table 3. An important conclusion from the analysis is that the large majority of variation in the choice to cycle is unrelated to physical characteristics of the commute route. Table 3, Column 5 suggests only 0.1% of the variation in cycling can be attributed to distance to work and the presence of hills. However, the magnitude of measured effects are relatively large and measured with high precision. Distance between home and work appears to be a significant factor. Correlatively (column 1), a 1 km increase in the distance to work reduces the probability of a worker commuting by bicycle by 0.020 percentage points. Considering only 0.40% of commuters choose cycling,

Table 3: Probability of a Worker Commuting by Bicycle, Worker Level Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Commute distance (km)	-.020**	-.014**			-.021**	-.014**
	(.00005)	(.00007)			(.00005)	(.00007)
Abs. Value Elevation change (100m)			-.068**	-.092**	.037**	-.007**
			(.0008)	(.001)	(.0008)	(.002)
Downhill to work (dummy)					.026**	.043**
					(.001)	(.002)
Home Tract Fixed Effects?	N	Y	N	Y	N	Y
Work Tract Fixed Effects?	N	Y	N	Y	N	Y
R^2	.0014	.0401	.0001	.0398	.0014	.0401

N = 84,775,768. Significance levels: $*$: 5% $**$: 1%. Robust standard errors in parenthesis.

the effect is large. Controlling away the confounding correlation between home and work location, the effect is somewhat reduced (column 2). Every km of distance is estimated to reduce the probability of commuting by 0.014 percentage points, representing a 3.5% reduction in the probability of choosing cycling.

The elevation difference between home and work is statistically significant, with large elevation changes negatively correlated with bicycle commuting (column 3). The result holds when home and work tract characteristics are controlled for (column 4). However, longer distance commutes naturally have larger elevation changes on average. When neighbourhood characteristics and commute distance are controlled for (column 6) I find the negative effect of elevation change remains significant and negative. Every 100m elevation change between home and work relates to a reduction in the probability of commuting by bicycle of 1.8%.

Finally, I find that the role of elevation change is asymmetric and that workers prefer to commute downhill to work and uphill to the home, rather than the converse. A worker is 10.1% more likely to bike to work if the elevation of the home is above the workplace, as oppose to the opposite configuration (Table 3, column 6). This may be because workers prefer not to engage in physical activity directly before work. For example, arriving at work after perspiring might be unappealing. Consistent with perspiration being a concern, Abraham et al. (2002) found workers are more likely to commute by bicycle if there are showers at their workplace. Other causes could be considered. For example, workers may face a commitment problem in which they would choose to commit themselves to exercise in the future, but when faced with the immediate task they would shirk responsibility (Strotz, 1955). Therefore, workers might commit in the morning to evening exercise, while being less likely to commit to immediate exercise in the morning.

The findings in Table 3 demonstrate that shorter, flatter commutes with the workplace downhill from the home are the most appealing for cycling. However, the three sources of topographical variation included in regressions explain almost none of the overall variation in worker's choice to cycle. The R^2 value for Table 3, column 5 is 0.0014. This finding supports the hypothesis that geography plays a very small role in explaining heterogeneity in cycling choice across individual commuters. The finding suggests that the geographic endowments faced by cities are not a core determinant of cycling uptake.

5 Conclusion

Prior research has argued that climate and topography play roles in the attractiveness of cycling as a commuting option. I use data on commuting flows, climate and elevation to estimate the roles of local geography on the probability a worker will commute by bicycle. Geographic characteristics do effect the probability of cycling, with dry, mild climates and flat topography leading to higher cycling rates. Despite statistically significant effects, the explanatory power of geography in predicting cycling is very low. I find climate can explain roughly a fifth of the variation in cycling uptake between metros and differences in hilliness have essentially no explanatory power. Within metros, the distance and hilliness of a commute faced by a worker explains less than 1% of variation in the probability of choosing to cycle.

The findings in this study have a potentially important lesson for policy: climatic and topographical endowments are relatively unimportant to the general uptake of cycling. Metros and routes that are seemingly unsuited for cycling do not have substantially lower rates of cycling. The exogenous conditions leading to heterogeneity in cycling rates appears to be related to local cultural predispositions and idiosyncratic individual preferences.

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