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Not So Fast: A Study of Traffic Delays, Access, and Economic Activity in the San Francisco Bay Area

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Not So Fast: A Study of Traffic Delays, Access, and Economic Activity in the San Francisco Bay Area

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16. ABSTRACT

he San Francisco Bay Area regularly experiences some of the most severe traffic congestion in the U.S. This past year both Inrix and the Tex ransportation Institute (TTI) ranked the Bay Area third only to Washington D.C. and Los Angeles in the time drivers spend stuck in traffic. T TI estimated that traffic congestion cost the Bay Area economy a staggering $3.1 billion in 2014 (Lomax et al., 2015). Such estimates are bas the premise that moving more slowly than free-flow speeds wastes time and fuel, and that these time and fuel costs multiplied over millions avelers in large urban areas add up to billions of dollars in congestion costs. But while few among us like driving in heavy traffic, do su easures really capture how congestion and the conditions that give rise to it affect regional economies? This study explores this question for t an Francisco Bay Area by examining how traffic congestion is (i) related to a broader and more conceptually powerful concept of access and (ow it affects key industries, which are critical to the performance of the region's economy.

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Executive Summary

While often overshadowed by traffic-choked Los Angeles to the south, the San Francisco Bay Area regularly experiences some of the most severe traffic congestion in the U.S. This past year both Inrix and the Texas Transportation Institute (TTI) ranked the Bay Area third only to Washington D.C. and Los Angeles in the time drivers spend stuck in traffic. Such rankings are widely viewed as badges of shame, tagging places as unpleasant, economically inefficient, even dystopian. Indeed, the economic costs of chronic traffic congestion are widely accepted; the TTI estimated that traffic congestion cost the Bay Area economy – by some measures the nation's most vibrant regional economy – a staggering $3.1 billion in 2014 (Lomax et al., 2015).

Such estimates are widely accepted by public officials and the media and are frequently used to justify major new transportation infrastructure investments. They are based on the premise that moving slowly than free-flow speeds wastes time and fuel, and that these time and fuel costs multiplied over millions of travelers in large urban areas add up to billions of dollars in congestion costs. For example, a ten mile, ten minute suburb-to-suburb freeway commute to work at 60 miles per hour might occasion no congestion costs, while a two mile, ten minute drive to work on congested central city streets – a commute of the same time but shorter distance – would be estimated to cost a commuter more than 13 minutes (round trip) in congested time and fuel costs each day.

But while few among us like driving in heavy traffic, do such measures really capture how congestion and the conditions that give rise to it affect regional economies? This study explores this question for San Francisco Bay Area by examining how traffic congestion is (i) related to a broader and more conceptually powerful concept of access and (ii) how it affects key industries, which are critical to the performance of the region's economy. It is a companion to a similar analysis of Metropolitan Los Angeles we completed in 2015 (Mondschein et al 2015), and includes comparative findings with the results of that study.

In a nutshell, we found in that study and now find in this one that road network delay is at best an indirect measure of the ease and quality of social interactions and economic transactions that are the bedrock of metropolitan areas and their economies. For example, a long distance trip to a grocery store in uncongested conditions on the outskirts of the region is not inherently superior to short distance grocery trip to the store in congestion, if both trips take about the same amount of time. Yet conventional measures of congestion delay would suggest otherwise. In central city areas, building densities are higher, which both pushes trip origins and destinations closer together and gives rise to traffic delays. So while high land use density is associated with increased traffic congestion, by allowing people and firms to locate in close proximity to a greater range of economic opportunities, such density helps to mitigate the effects of traffic congestion that its very presence engenders. Our analysis shows that in the Bay Area, more often than not, the time lost to commuter traffic delays in high-activity areas is more than off-set by the greater opportunities to reach destinations over shorter distances to which high development densities gives rise.

Emphasize Access not Mobility

Many residents are understandably wary of new development in their neighborhoods. The increased density caused by new construction generates new trips locally, which are often associated with increased traffic delays, especially in already built-up areas. The solution to most local residents is obvious: limit new development in congested areas and encourage growth elsewhere. But will pushing new development to outlying areas where travel distances tend to be much longer, or to other metropolitan areas all together, really make things better? Where one stands on this question depends very much on where one lives.

Contrary to popular wisdom, we find that the ability to travel quickly along roads is not associated with the ability to access economic opportunities in the San Francisco Bay Area. For example, living in parts of the region with relatively low levels of congestion does not, on average, increase accessibility to jobs – quite the opposite in fact. This is because the key to accessibility is the time and cost associated with reaching a desired destination; and travel time, in turn, is a function of both speed and distance, or proximity. By emphasizing *accessibility* (which is a function of both proximity and speed) within regional economies rather than *mobility* alone, our analysis produces more meaningful measures of the economic effects of traffic congestion. It's possible to reach great speeds on a "road to nowhere," but travelling at high speeds in and of itself does not meaningfully affect one's ability to reach work, friends, stores, or recreational activities.

What Does Congestion Mean for Commuters?

We find that, on average, more jobs can be reached in a given amount of time via the congested streets of San Francisco than on the fast moving freeways and boulevards in the fringes of the region. Put in general terms: as speeds on the road network increase for commuters in more remote parts of the regional economy, such mobility is more than canceled out by an associated lack of nearby destinations.

Figures 1 and 2 below display the contrasting effects of proximity and speed in determining accessibility to jobs in the Bay Area. In the left panel, we see that, as the number of jobs within 10 kilometers of where an individual lives increases, that individual's access to jobs also increases. By contrast, in (the mostly outlying) parts of the Bay Area where congestion levels are low and driving speeds are high, job accessibility (within 10 km) actually declines. The message from these charts is clear: high-density areas in the region provide better access to jobs, in spite of chronic traffic congestion, than those areas where traffic conditions are more often free-flowing.

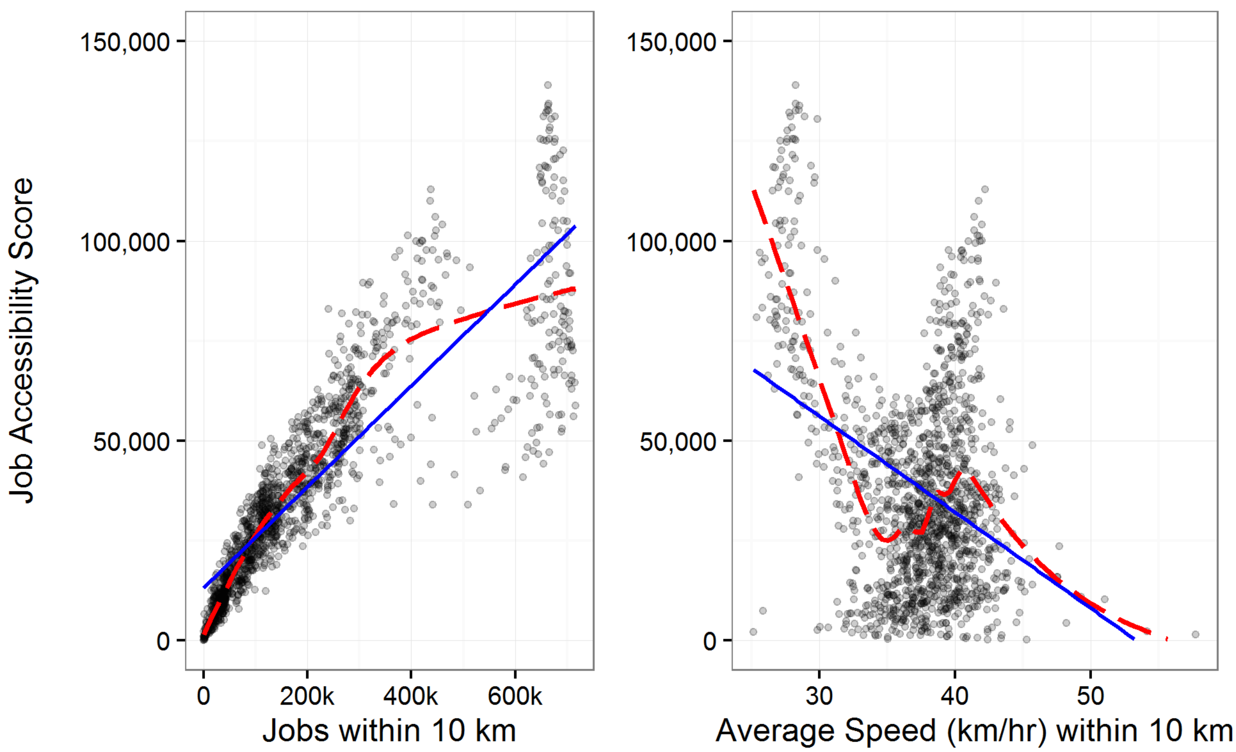

Figure 1 The Relationship between Proximity to Jobs and Job Accessibility (left) and Local Area Traffic Speeds and Job Accessibility (right) in the San Francisco Bay Area

While the above comparisons show that increased job density is associated with increased job access, and that *increased* average travel speeds are (perhaps counter-intuitively) associated with *decreased* employment access, they don't reveal how proximity and speed combine to produce accessibility. More specifically, they don't tell us the effect of traffic speeds in areas with similar levels of employment proximity. To examine these combined effects, we incorporated both speed and proximity as predictors in a multi-factor statistical model to simultaneously account for within and between county effects of traffic on employment access. The results of this statistical model are displayed in Figure 2, which shows that the effects of proximity (i.e. nearby jobs) on overall job accessibility are far greater than the effects of faster travel speeds due to lower levels of congestion – whether looking within or between counties in the Bay Area. Figure 2 also shows that differences in speed and proximity within counties matter relatively little compared to the county-level averages. The statistical models we ran, however, showed that within-county differences mattered more in some places than others. Namely, we found that in Santa Clara and San Mateo Counties (which are together Ground Zero for the global IT industry), increases in travel speeds had a larger effect on increases in accessibility – although, even here, the effects of job proximity outweighed the effects of speed on job access by a wide margin.

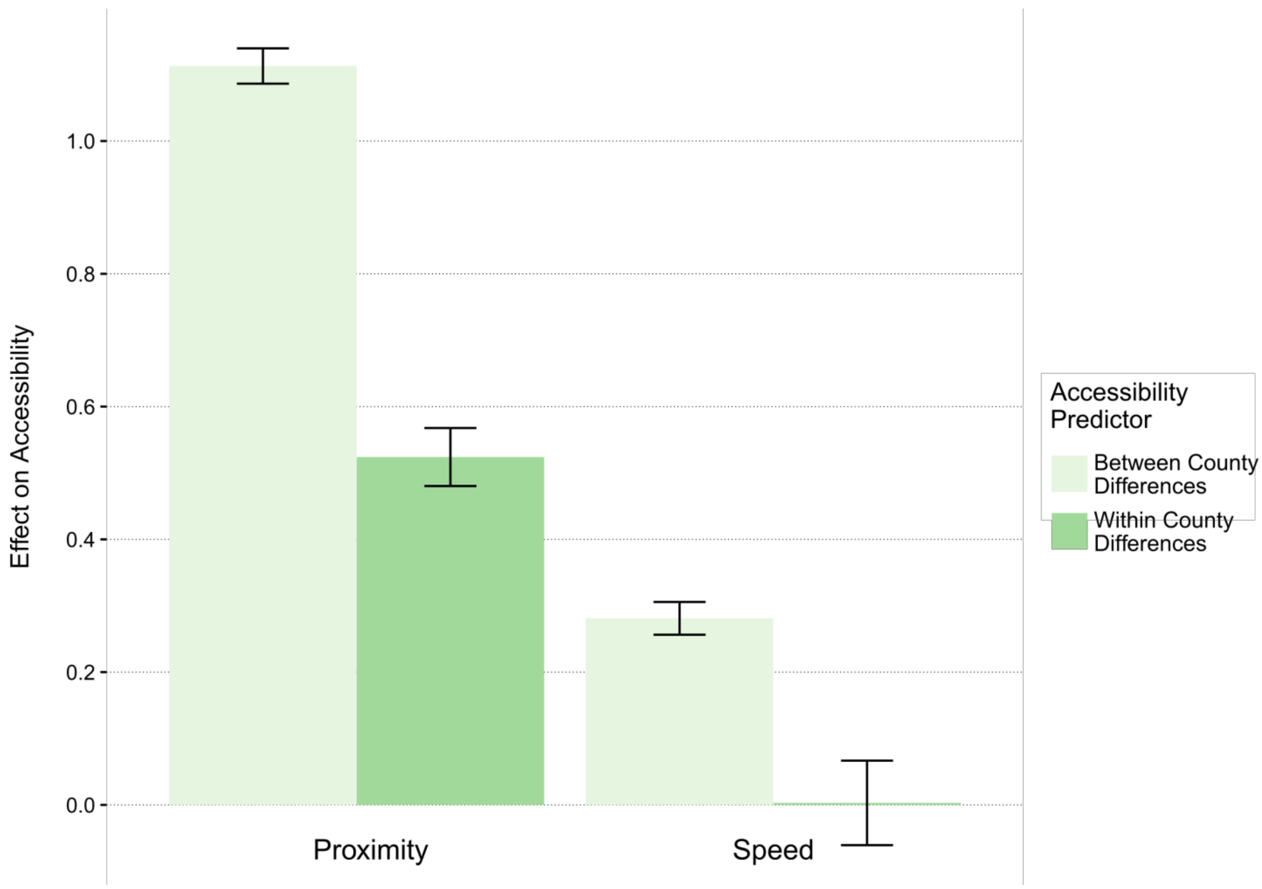

Figure 2 The Relative Effects of Differences in Proximity and Speed on Overall Job Accessibility in the San Francisco Bay Area.
Note: Error bars display 95% confidence interval for proximity and speed effect sizes.

What Does Congestion Mean for Firms?

Just as commuters use the road network to access jobs, firms use road networks to access their suppliers, labor, customers, and peers. One key feature of national economies is the extent to which different regions specialize in the production of different goods and services (such as finance in New York and automobiles in Detroit). A key feature of such regional specialization is the extent to which thousands of firms and workers of the same industry cluster in close proximity to one another for productive advantage. These "economies of agglomeration" among peer firms in economic sectors that export most of their goods and services to other regions for consumption are now widely viewed as key drivers of regional economies. The entertainment, information technology (IT), and securities industries in the Bay Area are three exporting industries cases in point.

With the high-profile exceptions of Pixar in Emeryville in the East Bay and Skywalker Ranch in Marin County, entertainment sector employment in the Bay Area overall is highly concentrated in the very densely developed and chronically congested city of San Francisco. So while we should expect, all things equal, that traffic delays will affect the ability of these agglomerated peer firms to interact (access) with one another, inter-firm access is jointly determined by both traffic delays and proximity, and not delays alone. This explains why we find that the incidence of entertainment firm start-ups in the Bay Area is highest where traffic speeds are *lowest*. Thus, in the Bay Area entertainment sector, traffic delays are actually associated with more new firm start-ups, and not less. It's not that the congestion is motivating new entertainment start-ups; rather, these start-ups are tending to locate in areas (such as San Francisco) where access to other entertainment firms is high (due primarily to proximity) in spite of congestion.

But the IT industry (that is the principal driver of the Bay Area economy), by contrast, is centered in the decidedly suburban "Silicon Valley" in Santa Clara County 80 kilometers south of San Francisco. In contrast to the transit-rich and walk-friendly City, the car is king in Silicon Valley and traffic endemic. And while traffic delays have relatively little effect on employment accessibility in San Francisco, traffic speeds exert a substantially larger influence on accessibility in Silicon Valley. As a result, and in contrast to the Bay Area entertainment industry, traffic speeds are positively associated with IT firm start-ups in the Bay Area. This more intuitive result makes sense in a suburban context where nearly all trips are by car and fewer traffic delays unambiguously mean higher levels of access.

To show the effects that same-sector employment proximity and speed have on the likelihood of new firm starts in various Bay Area economic sectors, we estimated a set of statistical models of how proximity to other firms and area traffic speeds affect the likelihood of new firm starts (while statistically controlling for a number of other factors known to influence start-ups). Figure 3 shows the estimated likelihood of new firm start-ups across the Bay Area. Each dot represents the estimated effect of a one-standard-deviation increase in travel speed (red dots) or same-sector employment proximity (blue dots), while controlling for a number of neighborhood features and holding them at their average values. These graphs show that for each of the five sectors that we examined, being close to a greater amount of same-sector activity matters significantly more than being able to travel swiftly.

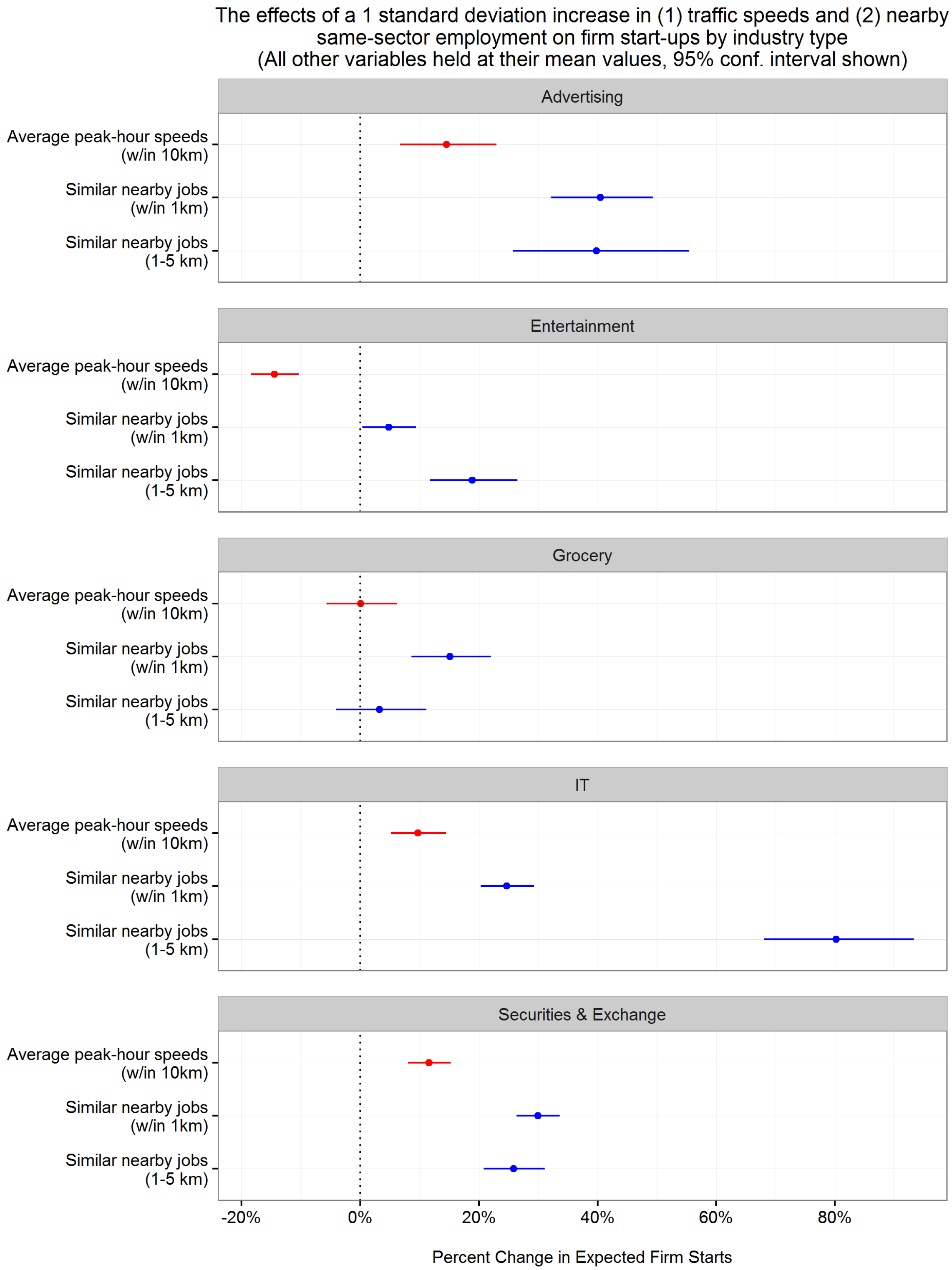

Figure 3 The Effects of Same-Sector Employment Proximity and Average Area Traffic Speeds on the Likelihood of New Firm Starts in the Advertising, and Securities Industries

Note: Employment figures shown here are logged.

Policy Implications: The Congestion Conundrum

Our analyses of employment accessibility and firm start-ups in the Bay Area, and our companions to these analyses conducted for Los Angeles (Mondschein, et al., 2015) present something of a congestion conundrum: access, both for commuters to jobs, and for firms to other firms within given industries, is often greatest where traffic is heaviest. As a result, the benefits of proximity in densely developed environments appear to generally and consistently outweigh the costs of traffic congestion that such dense development typically entails. Such findings suggest that the congestion calculations proffered by Inrix and the TTI discussed at the outset are incomplete at best, and misguided at worst. Measuring the costs of traffic delays, infuriating though they may be, without netting them against the access benefits of clustered trip origins and destinations common in (though by no means guaranteed by) densely developed settings paints a decidedly incomplete picture of the ways that cities like San Francisco facilitate social interactions and economic transactions. Determining access by measuring traffic delays alone is akin to determining the area of a rectangle by measuring only its width.

As noted above, the novel research presented in this report complements our recently completed, similar study of metropolitan Los Angeles (Mondschein et al, 2015) and adds considerable support to the growing chorus of voices arguing for a shift from a mobility-focused view of how urban transportation networks perform, to an access-focused view of what urban systems (including transportation systems) do. Mobility – in cars, on trucks, via public transit, and by bike and foot – is a *means* to access, not an *end* in itself. This shift in perspective is integral to the smart growth urbanist movement touted by many urban designers and planners. Beyond their direct implications for planners and policy makers, our findings offer insights for how transportation and land use decision makers might evaluate new development proposals to consider, not just traffic impacts, but on how they affect neighborhood, sub-regional, and regional accessibility.

While our work directly challenges the local traffic impact logic of evaluating development proposals, by no means do we suggest that traffic occasions no costs on regions, firms, and households, or that there is no merit to traffic mitigation. Our analyses also show that, within a given area (be it a high-access central area, or a relatively low-access outlying area), fewer traffic delays are better, all things equal – particularly in the Silicon Valley sub-region. Such findings suggest that efforts to optimize signal timing, variably price parking and road capacity, increase capacity at severe traffic bottlenecks, and improve alternatives to driving in traffic (such as via public transit, biking, and walking) are typically worthy endeavors. What our analysis does suggest, however, is that a myopic focus on the traffic impacts of new developments is misguided and may actually decrease accessibility and economic activity in an effort to protect traffic flows.

Table of Contents

Table of Figures

Acknowledgments

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Andrew Mondschein is an Assistant Professor of Urban and Environmental Planning at the University of Virginia. He focuses on transportation and how transportation systems facilitate urban goals such as access to opportunities, sustainability, and community building. Recent research includes topics such as how people cope with congestion, the role of information technologies in travel behavior, the demographics of walking, and how people experience cities through everyday transportation. He holds a PhD and MA in Urban Planning from UCLA and a BA in Architecture from Yale University. Prior to pursuing his PhD, he was an Associate at Gruen Associates, a Los Angeles planning and architecture firm where he specialized in transportation and land use projects including the Orange Line Bus Rapid Transit corridor.

Taner Osman is a postdoctoral researcher in the Lewis Center for Regional Policy Studies and lecturer in the Department of Urban Planning at UCLA. His research specializes in understanding differences in economic prosperity within and across metropolitan regions. He is a co-author of the recent book "The Rise and Fall of Urban Economies," published by the Stanford University Press. He holds a PhD in Urban Planning from UCLA and an MA in Regional Economic and Social Development from the University of Massachusetts.

Brian D. Taylor is a Professor of Urban Planning, Director of the Institute of Transportation Studies, and Director of the Lewis Center for Regional Policy Studies at UCLA. Professor Taylor has nearly 200 publications and other pieces of written work (over 80 of which are peer reviewed) on transportation policy and planning topics relating to travel behavior, transportation economics and finance, social equity, and the politics and history of transportation planning. Prior to joining the UCLA faculty in 1994, he was on the City & Regional Planning faculty at the University of North Carolina at Chapel Hill, and before that he was an analyst with the San Francisco Bay Area Metropolitan Transportation Commission. He holds a PhD in Urban Planning from UCLA, an MS in Civil Engineering and an MCP in City & Regional Planning from UC Berkeley, and a BA in Geography from UCLA. Professor Taylor was elected to the College of Fellows of the American Institute of Certified Planners in 2012 and he despises driving in heavy traffic.

Trevor Thomas is a PhD student at UCLA, focusing on the social and economic impacts of transportation. He has participated in a number of research efforts, examining the transportation cost burdens felt by low-income households, changes in travel behavior over the course of the Great Recession, and the potential effects of infrastructure investments on gentrification and residential displacement. Before coming to UCLA, he was an associate transportation planner for the Southwest Michigan Planning Commission. He holds an MUP in Urban Planning and a BSE in Aerospace Engineering, both from the University of Michigan, Ann Arbor.

Chapter 1: Introduction

Does chronic traffic congestion impede the economic performance of metropolitan areas? This seemingly obvious question is a remarkably difficult one to answer. Because it increases time and costs relative to free-flow travel, how could traffic congestion *not* hinder regional economies? Congestion slows the flow of people and goods, making trips take longer and arrival times more uncertain. Time spent in traffic is often time that could otherwise be spent doing something productive for drivers, passengers, and even goods. Vehicle fuel efficiency generally declines in heavy traffic, while vehicle emissions per mile go up. And who hasn't commiserated with friends and colleagues about that miserable drive over the Bay Bridge, a slow crawl in a San Francisco Uber car, or that nightmarish drive over the mountains to Santa Cruz one holiday weekend?

Driving in traffic is a mostly negative and decidedly visceral experience, which perhaps clouds our judgment about its effects. Still, the conceptual links between transportation and economic activity are intuitive. Transport is so central to all economic activity – in moving raw materials to factories, labor to worksites, inputs and outputs along supply chains, consumers to services, and products to consumers – that studying the role of transportation in the economy may seem to some an exercise in the obvious. What is less obvious, however, is how delays on road networks induced by traffic congestion affect the performance of local economies. Economic activity and traffic both vary at small scales, so the effects of traffic congestion in the San Francisco Bay Area, like in many big metropolitan areas, are in fact likely to vary significantly among communities within the region, and among sectors of the economy as well.

Metropolitan areas exist largely because they facilitate economic transactions and social interactions among firms, households, and individuals, and the transportation network directly affects the quality and cost of these interactions. Thus, delays on road networks should reduce regional economic efficiency. Transportation network delay is, by definition, a suboptimal outcome since households and individuals travel to destinations at speeds slower than they would be able to in relatively free-flowing conditions – though free-flowing conditions are often hypothetical rather than attainable, absent mechanisms to ration scarce road space. In the context of the economy, traffic delay is a cost to people and firms. These costs include higher fuel consumption and emissions per mile of travel, higher job access costs for workers, and increased firm costs for (a) distributing products and services to consumers, (b) accessing networks of suppliers and consultants, and (c) receiving production inputs, which is particularly significant in time-sensitive supply networks. While the possible effects of congestion on economic productivity are many, analysts have actually struggled to measure the cost of congestion on economic performance and there is currently nothing close to a consensus on the issue (Glaeser & Kohlhase, 2004; Hymel, 2009; Sweet, 2011; 2014a). The current state of research in this area is considered in detail in the second chapter of this report.

Given these many costs of congestion, reducing traffic delays should, in theory, improve regional economic performance. Such theory is the basis for many public officials' efforts to invest public dollars to reduce traffic delays. This theory assumes, however, that there are no indirect benefits to congestion or, more accurately, that there are no benefits to the places and activity in those places that give rise to congestion. This is a very big, albeit common, assumption to which we devote considerable time and effort to excavate in this report. We examine in the pages that follow whether the relationship between traffic congestion and economic performance, both conceptually and empirically, is considerably more subtle and complex than the standard "faster-is-better" refrain would suggest.

Transportation network delay is, at best, an indirect measure of the ease and quality of transactions and interactions in a regional economy. A more accurate measure of the effects of congestion on the interaction among firms and individuals is *access*, which refers to the ability of people and firms to avail themselves of economic and social opportunities in space. Accordingly, this study examines how traffic congestion affects economic performance in the San Francisco Bay Area in 2010 (the most recent year for which modeled data were available) using data on traffic and vehicular flows from the Metropolitan Transportation Commission. Ultimately, we aim to identify where and under what circumstances congestion appears to depress, have no effect, or is associated with increased economic productivity in the Bay Area region.

The role of congestion in economic development is not simply an academic enquiry. Claims that traffic congestion is a significant drag on metropolitan economies are rarely supported with evidence, yet they are used to justify enormous public expenditures on urban freeways, rail transit systems, and many other forms of transportation infrastructure. In the Bay Area, current and planned spending on projects to address traffic congestion are everywhere, from the growing Express Lanes system to extensions of BART and CalTrain. Voters, tired of traffic, have often willingly funded new expenditures, approving state and local bond initiatives and sales tax increases to "fix" the traffic problem. Even policies that may pay for themselves, such as SFPark, are predicated on the idea that they can tame traffic and support local economic activity. This report can help Bay Area residents and decision-makers better understand whether and how congestion such efforts can benefit the regional economy.

1.1 The Congestion Conundrum

Traffic often moves slowest in the most centrally located and densely developed districts, and fastest in peripheral areas where origins and destinations are widely spaced. This presents a conundrum that can be illustrated by a simple example. Two workers, one a city dweller and the other a suburbanite, can experience very different levels of *mobility* due to traffic congestion, yet have very similar levels of *access* to their respective workplaces. In this example, the city dweller averages just 12 miles per hour driving in heavy traffic each morning to her job four miles away, while the suburbanite averages a speedy 60 miles per hour on his mostly freeway trip to work in an adjacent suburb 20 miles away. While the effects of traffic congestion on their commutes are unambiguously different, the relative proximity of work for the city dweller offsets the much slower travel time; each spends an average of 20 minutes commuting to work, and each enjoys similar levels of job access, albeit very different levels of transportation mobility.

As this example suggests, the speed of vehicular travel is not an end in itself, but is instead a means to an end – in this case, of getting to work. As we will see in the chapters that follow, the parts of the Bay Area that enjoy the highest average travel speeds are typically located in the lowest density areas with the fewest nearby destinations, while dense hubs of activity that regularly host clogged, slow-moving roadways have the most nearby destinations. Whether an individual has better job access in outlying areas with fast-moving traffic or in central areas with chronic congestion is an empirical question that we examine in this report.

Conventional wisdom, particularly among urban and transportation planners in the 2000s, is turning away from the long-established focus on travel speeds as the primary means of facilitating interactions. It is instead emphasizing *access* to destinations, which frames transport as a means to social interactions and economic transactions, rather than an end in itself (Grengs, 2010; Kawabata & Shen, 2006; Shen, 2001). The capacity to access destinations is a function of speed, but also of destination proximity, which is determined by land use patterns and the built environment. As noted above, while higher travel speeds and a greater density of nearby destinations each contribute to higher accessibility levels, the two factors often times work at cross purposes. This nuanced framework for understanding the consequences of travel delay will provide the basis for understanding the impact of traffic congestion on the performance of industries in the Bay Area economy. We hypothesize that access, rather than network delay (congestion), better explains the extent to which the transportation network affects economic performance.

1.2 Congested Development?

To examine and better understand the links between traffic speeds, proximity, and economic development, we begin by reviewing the two, largely distinct research literatures on these topics. We then conduct two complementary analyses using data for the San Francisco Bay Area. The first examines the relationship between travel speeds and proximity across neighborhoods in the Bay Area, and the second examines the relationship between travel delays and new business starts in the advertising, entertainment, grocery, information technology, and securities and commodities industries.

We hypothesize that the performance of industries, and by extension, regions, is highly dependent on the particular configuration of land uses and corresponding transportation systems, and not simply on levels of network delay. Put another way, the economies of clustering and agglomeration may outweigh the negative effects of local congestion within the regional economy; we test this proposition empirically.

This study adds to a nascent body of research on the impact of traffic congestion on economic performance since it tests whether the effects of traffic congestion are uniform across regional economies and examines under what circumstances the negative economic effects of roadway delays might be mitigated by the economic benefits of agglomeration. Our goal with this work is to help public officials and government analysts to move past simple notions of the traffic congestion/economic competitiveness link to understand where and under what circumstances traffic delays impede economic performance, and where they may actually coincide with *improved* economic performance in spite of delays.

1.3 The San Francisco Bay Area as a Research Venue

The San Francisco Bay Area is today one of the most dynamic regional economies on the globe, and is the world's leading hi-technology center. The impressive list of companies that call the region home – from Hewlett Packard and Intel, to Facebook and Google, to the world's richest corporation, Apple – and the region's economic success spanning multiple decades make the Bay Area the envy of local public officials around the world. Ranked by population, the San Francisco Bay Area is the fifth largest metropolitan area in the U.S., with 7.2 million residents.

In addition to the high-tech suburbs of "Silicon Valley" in the southern part of the region, the Bay Area is also home to world-renowned vineyards and wineries in Napa and Sonoma counties to the north (see Figure 1.1). To the west is a scenic, jagged, and lightly populated coastline, and to the east are suburban valleys of Alameda and Contra Costa Counties below mountains that separate the region from the Central Valley of interior California. As the region grows, the Bay Area is increasingly spilling out into the Central Valley to the east and northeast. The region's counties orbit the City of San Francisco, a densely populated, peninsular city, renowned for its liberal spirit, beautiful neighborhoods and architecture, and hilly terrain. The region's major cities are the City of San Jose, with more than one million inhabitants, the City of San Francisco (with about 850,000 residents), and the City of Oakland (with a little more than 400,000 residents). The region is the wealthiest in the nation in terms of per capita income, and the gross metropolitan income is $575 million. If the region's 7 million inhabitants were a nation, it would the world's 22nd largest economy, just below Argentina and above Sweden (Storper et al. 2015).

According to the most recent Urban Mobility Report published by the Texas Transportation Institute (Lomax et al., 2015), San Francisco ranks a close third as most congested region in the nation, behind only Washington D.C and Los Angeles. On average, Bay Area commuters "waste" 78 hours per year to traffic congestion, compared to 82 hours for their counterparts in the nation's capital, and 80 hours in Los Angeles. The size and diversity of the Bay Area economy, and its ranking as one of the most congested regions in the U.S., makes it the ideal case study for an exploration of the links between traffic delay and economic performance.

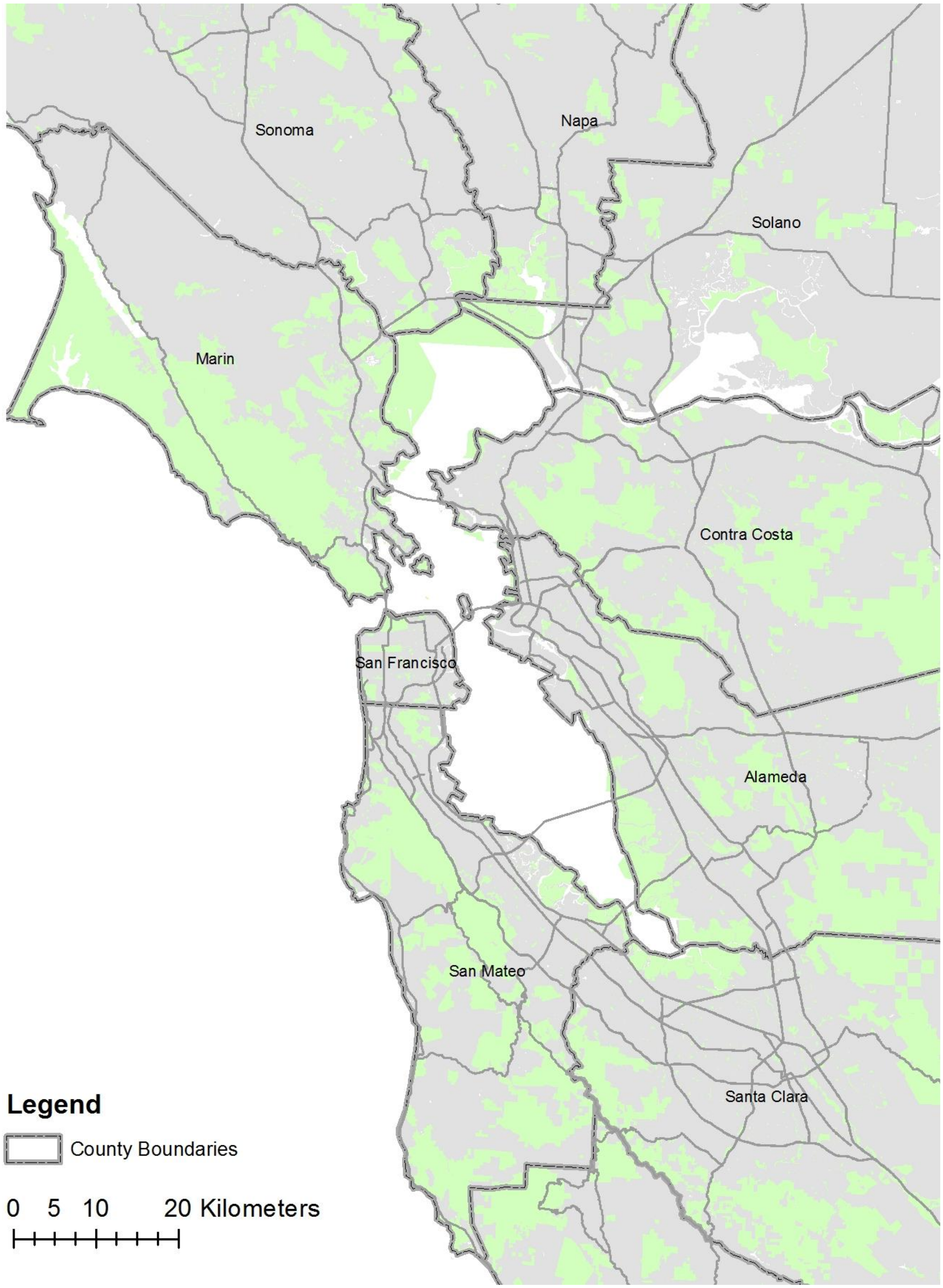

Figure 1.1 9-County Bay Area Study Area

In 2009, approximately 3.25 million people were employed in the region, according to the Quarterly Census of Employment and Wages (Bureau of Labor Statistics, 2009), with an average per capita salary of $66,290 – the highest of any large metropolitan area in the nation. This study will focus on the performance of five industries within the regional Bay Area economy. These industries were chosen to represent "exporting" sectors within the regional economy. These are goods and services that are primarily consumed outside of the Bay Area. These industries represent an array of sectors where the nature of production varies significantly, and which cover the spectrum of wages paid within the region. Table 1.1, below, describes total employment and the average annual salary in the Bay Area for each industry of investigation in this report.

Table 1.1 Descriptive Statistics for Key Industries

	Advertising	Enter-tainment	Information Technology	Securities and Commodities	Grocery Stores
Total 2009 Employment	22,558	11,020	346,523	59,523	69,189
Average Annual Salary	$80,921	$80,963	$125,638	$239,865	$29,333

1.4 Roadmap

The remainder of this report proceeds as follows. Chapter 2 reviews the primary theories and past empirical studies of regional economic performance, traffic congestion, and the links between the two. Chapter 3 examines the relationships between speed and proximity in determining employment access across cities and neighborhoods in the San Francisco Bay Area. Chapter 4 then examines how traffic congestion affects the location of new business establishments in the regional economy for a cross-section of industries, and Chapter 5 summarizes and considers the significance of the findings of this report. While this analysis focuses on the Bay Area, a parallel analysis we have completed for the

Southern California region facilitates a comparative discussion of our findings between the two regions. The full Southern California analysis is available under separate cover in the report "Congested Development: A Study of Traffic Delays, Access, and Economic Activity in Metropolitan Los Angeles." (Mondschein et al. 2015)

Chapter 2: Literature Review

Prior research on the effects of traffic congestion on economic activity and productivity comes from a broad set of intersecting disciplines, including transportation planning, travel behavior research, urban economics, economic geography, behavioral economics, and social psychology. Our review of the literature focuses on the key concepts that inform our research questions, shared across those disciplines. Those concepts include:

- Traffic congestion
- Access
- Firm location
- Agglomeration
- Quality of life

This previous research helps define these phenomena and how they may interact. Ultimately, the literature suggests that firms may respond to traffic congestion with a diverse set of actions, each action potentially having its own effects on both the firm and regional economic productivity. In sum, we conclude that the literature on congestion-impeded access and firm location decisions is underdeveloped, and our empirical analyses presented in Chapters 3 and 4 seek to address this gap in the literature.

2.1 Congestion and Accessibility

2.1.1 Defining Traffic Congestion

Traffic congestion occurs when the demand for road space exceeds its supply in a given direction at a given time in the day. This imbalance between supply and demand creates a scarcity of road capacity; as more individuals use a relatively fixed supply of road capacity, less space is available for travel by others and queuing for the scarce capacity occurs. Absent some form of variable road pricing or some other rationing schema (to bring the demand for travel in line with supply), road scarcity is signaled by lower and more variable travel speeds than would be the case during free flowing conditions. Traffic congestion, therefore, typically refers to travel delay on road networks caused by vehicles upstream and is measured in numerous ways: average peak-period speeds on links in the transportation network, so-called “level of service” calculations (most typically applied to intersections), and, increasingly, the additional amount of time required to travel during peak periods relative to off-peak, free-flow speeds, or posted speed limits (Bertini, 2006).

The long-term causes of traffic congestion are numerous and include (i) population and/or job growth rates that exceed the growth of road supply, (ii) increasing incomes and/or decreasing auto operating costs, (iii) concentration of economic activities in locations and at times that concentrate traffic flows, (iv) low-density/auto-oriented development, and (v) limited alternatives to motor vehicle travel (Taylor, 2002). Varying combinations of these factors have ensured that traffic congestion has increased over time in most metropolitan areas. In addition to these long-run causes of delays, there are short-term causes of congestion as well, such as crashes, construction projects, inclement weather, and special events (Downs, 2004).

Measurement of traffic flows and delays is a core part of transportation engineering and planning practice, but in general has tended to emphasize two distinct types of metrics: (1) highly localized individual transportation network link and intersection measures (which are most common) and (2) area- or region-wide indices of delay. Level of service measures and volume/capacity ratios are examples of the former, while the widely-cited Travel Time Index touted by the Texas Transportation Institute is an example of the latter (Schrank, Eisele, & Lomax, 2012; Ye, Hui, & Yang, 2013). While separated in scale, both types of measures emphasize speed or reductions in speed on the network without taking travel alternatives or impacts on travelers’ accessibility into account (Mondschein, Taylor, & Brumbaugh, 2011; Ye et al., 2013). Researchers have increasingly highlighted the importance of considering traffic congestion's effects not only on delay, but on interactions among delay and individual and firm choices, and economic and quality of life outcomes (Mondschein et al., 2011; Kwan & Weber, 2003; Glaeser & Kahn, 2004; Sweet, 2011). In other words, they call for a linkage between direct measures of network delay, and indirect measures of congestion's effects on the economic development and performance outcomes described above.

In response, both policymakers and transportation practitioners have begun to shift from an analytical emphasis on network-measured delay alone, especially if those measures are seen as detrimental to broader public policy objectives such as accessibility or sustainability. Perhaps the most notable example of this is the recent passage of legislation in California to end the use of roadway level of service impacts as a central component of state-mandated environmental impact analyses (DeRobertis et al., 2014).

2.1.2 Access

Conventional wisdom, particularly among urban and transportation planners in the 2000s, is turning away from the long-established focus on travel speeds as the primary means of facilitating interaction. It is instead emphasizing *access* to destinations, which frames transport as a means to social interactions and economic transactions, rather than an end in itself (Grengs, 2010; Kawabata & Shen, 2006; Shen, 2001). The capacity to access destinations is a function of speed, but also land use patterns and the built environment, such as the array and proximity of destinations from a given place. As noted above, while higher travel speeds and a greater density of nearby destinations each contribute to higher accessibility levels, the two factors frequently work at cross purposes. This nuanced framework for understanding the consequences of travel delay will provide the basis for understanding the impact of traffic congestion on the performance of industries in urban economies.

Mobility, whether by motor vehicle, bus, train, bicycle, or foot, enables the social interactions and economic transactions central to urban life. But while mobility is a central component of providing people and firms with access to one another, it does not follow that more mobility means more access. Accessibility is a popular and variously defined term that centers on the ability of travelers to avail themselves of economic and social opportunities in space. It is possible to reach great speeds on a "road to nowhere," but travelling at high speeds in and of itself does not meaningfully affect one's ability to get to work, friends, stores, or recreational activities. In this context, mobility – the speed at which it is possible to travel – is a "means" of travel, whereas access is considered an "end" of travel, and refers to the actual opportunities to reach desired destinations.

Within a given regional economy, traffic delays not only vary substantially from one place to another, but also are likely to inhibit social and economic interaction in some places more than in others. Major causes of variable effects of similar levels of delay across space include (i) the density of land use, (ii) the characteristics and capacity of the transportation network, (iii) the particular nature of delays on the network, (iv) the desires and resources of delayed travelers, and (v) how these four elements interact. For example, Mondschein et al. (2011) found that in Los Angeles and Orange County, some neighborhoods are better "congestion-adapted" than others, since they host higher levels of individual activity participation in spite of relatively large traffic delays. This is because in some places, less vehicle travel (due to short travel distances, and ease of walking, biking, and transit travel) is required to access an equivalent range of opportunities *ceteris paribus*. Assuming accessibility to be largely a function of speed may lead us to inappropriately prioritize congestion reduction at the expense of spatial (land use) arrangements that may more effectively improve accessibility in some (or perhaps many) places. Within the context of this study, we investigate whether traffic congestion affects economic performance more in some parts of a regional economy than in others, and under what conditions such differences arise.

2.2 Economic Geography and Transportation

2.2.1 Agglomeration: Concentration and Specialization

There are two ideas central to the study of economic geography that are also pertinent to this study: concentration and specialization. With respect to concentration, Desilver (2014) estimates that six U.S. metropolitan areas in 2014 accounted for about one quarter of the entire economic output of the United States: New York, Los Angeles, Chicago, Washington DC, Dallas, and Houston[1]. Relatedly, a 2009 study found that 68 percent of the U.S. population in 2000 lived on 1.8 percent of its land (Glaeser & Gottlieb, 2009). Likewise, a 2004 study estimated that 75 percent of Americans live in cities that comprised just 2 percent of the country's land area (Rosenthal & Strange, 2004). The overarching point of these studies is both clear and unambiguous: people and economic activity are tightly bound together in space and concentrated in relatively few locations.

In addition, regions specialize economically in the production and export of different goods and services. No city in the United States specializes in supermarkets or gas stations, but metropolitan areas specialize in "basic" (also referred to as "tradable") industries like information technologies (the San Francisco Bay Area), entertainment (Los Angeles), finance (Manhattan), and automobiles (Detroit). Critically, the goods and services in which a region specializes, to a large extent, determine regional prosperity (North, 1955; Krugman, 1991; Krugman & Obstfeld, 2003; Moretti, 2012).

The transportation network, along with the concept of "increasing returns," is central to formal economic models of "agglomeration economies," which is the study of why economic activity shows a high degree of geographic concentration (Krugman, 1991, 1998). Cities are expensive places to live and do business, so why do people and firms crowd into them? Land is scarce and expensive (Cheshire, Nathan, & Overman, 2014), and so-called "negative externalities" like traffic congestion and air

[1] Such estimates can vary depending on how one defines a metropolitan region. Please note that this estimate relates to metropolitan statistical areas (MSA) rather combined statistical areas (CSA). MSA definitions, for example, consider San Francisco and San Jose to be separate metropolitan areas.

pollution are commonplace. To endure such diseconomies of agglomeration (the costs of crowding together), people and firms must receive some offsetting benefit from locating in cities, which are known to increase returns to production (Krugman, 1991; Duranton & Puga, 2004). Otherwise, why go to the trouble and expense to live or locate a business in built up, congested areas?

Increasing returns to production, and the related idea of "economies of scale," describe how the production of a particular good or service becomes more efficient and cheaper as the scale of production increases. Toyota must spend hundreds of millions of dollars up front to design and build the first Corolla, but when those up-front costs are spread over hundreds of thousands of Corollas, the economies of scale make the Corolla an affordable car. Scale economies can be realized in many ways, including from spatial clustering. By clustering together in space, firms in certain industries are able to reduce the cost of, and increase the efficiency in, accessing industry specific workers and input suppliers, which are positive externalities of such clusters (Krugman, 1991). Furthermore, such spatial clustering enhances "information spillovers" (sometimes referred to as the "the secrets of the trade"), which are often associated with frequent face-to-face interaction among employees of different firms in the same industry, as the flow of information has been shown to display more friction with increased distance (Marshall, 1961; Jaffe, Trajtenberg, & Henderson, 1992; Feldman, 1994).

Transportation costs are as important as increasing returns to understanding why economic activities cluster in space. If transportation costs are high, they offset the economic benefits of clustering. As transportation costs fall, however, inter-regional trade emerges (Krugman, 1991). Due to increasing returns and transportation costs that have steadily fallen over the past two centuries, it is today cheaper and more efficient to produce the goods and services of some (tradable) industries in one, or very few places, and then transport them to markets around the world, than it is for each place around the world to produce a full range of goods and services locally (Glaeser & Kohlhase, 2004).

Until quite recently, it was widely assumed that agglomeration economies were region-wide in scope (Rosenthal & Strange, 2003, 2010). In other words, as long as two firms of the same industry were in the same region, their agglomeration benefits would manifest regardless of whether they were on the same block or located 50 kilometers apart. These assumptions were not tested for many years because fine-grained data were not easily available at sub-metropolitan scales. However, recent research using better data finds that agglomeration economies attenuate over much shorter distances than previously thought – as little as a single kilometer (Arzaghi & Henderson, 2008; Rosenthal & Strange, 2010).

Conceptually, it stands to reason that agglomeration economies attenuate both regionally and locally. With respect to specialized labor market access, the scale of so-called commute sheds (which roughly cover the area accessible within an hour of peak direction travel) argue for metropolitan scale agglomeration economies. By contrast, firm-to-firm interactions and knowledge spillovers appear to attenuate much more locally. In both cases, transportation networks (both regional and local) are critical to regional prosperity, both by moving workers, goods, and consumers, and by facilitating inter-firm agglomeration economies. Thus, transportation networks are critical to the scale and efficiency with which firms and employees in basic (or "tradable") industries are able to interact and transact with one another. Despite the conceptually central role that transportation networks play in facilitating agglomeration economies at multiple scales, urban economists and economic geographers have largely been silent on the empirical effects of traffic congestion on the performance of regional economies, either among or within regions, where both transportation systems and traffic delays vary greatly over space.

2.2.2 Perspectives on Transportation and Economic Development

Transportation networks have long played, and continue to play, a vital role in the economic development of cities and countries. Transport is central to all economic activity – in moving raw materials to factories, labor to worksites, inputs and outputs along supply chains, consumers to services, and products to consumers. Within regional economies, the emergence of streetcars and various forms of rail infrastructure (in addition to modern elevators) were a major contributing factor to the rise of central business districts and the growth of cities in the late nineteenth and early twentieth centuries (Muller, 2004; Bruegmann, 2006). Such infrastructure enabled the development of residential neighborhoods further from central business districts than was previously possible. Thus, transportation systems determine the extent of labor markets (since they enable more people traveling at greater speeds to access employment over greater distances) and enable cities to expand in size (Giuliano, Agarwal, & Redfearn, 2008; Drennan & Brecher, 2012). Since scope and scale economies broadly mean that the size of cities is strongly correlated with productivity and economic growth (Duranton & Puga, 2004; Cheshire et al., 2014), transportation networks play a crucial role in shaping regional, and by extension, national prosperity.

To this end, the provision of transportation infrastructure has been a widely used economic development policy tool to foster growth in underperforming regions, both within the U.S. and globally (Pike, Rodríguez-Pose, & Tomaney, 2006; Cheshire et al., 2014). In one of America's grand experiments in regional development, 70 percent of all Appalachian Regional Commission funds spent to develop the region were spent on the construction of new highways to better connect the then relatively isolated region to other parts of the country (Isserman & Rephann, 1995; Singerman, 2008). Increasing access from the region to other, more prosperous places, it was believed, would enable Appalachian producers to benefit from increased market access and generate economies of scale in local production. But, of course, this increased access also opened up Appalachian consumer markets for cheaper goods produced elsewhere. This so-called "two-way roads problem" highlights that, while roads do indeed enhance access from poorer regions to other places, they also increase competition for previously shielded local industries, which can be damaging for uncompetitive local producers (Cheshire et al., 2014).

While transportation is necessary for economic development, it is of course not alone sufficient. Indeed, transportation infrastructure investment has long been a popular economic development tool in declining, once-prominent urban economies, such as Buffalo, Detroit, and a myriad of other cities (Euchner & McGovern, 2003). On balance, however, investment in transportation infrastructure in such economies has proven to be an ineffective urban development tool (Cheshire et al., 2014). In such places, inadequate transportation was not the only barrier to economic growth, and perhaps not even a barrier at all. With respect to traffic congestion, places underperforming economically are, almost by definition, places with relatively low levels of traffic congestion. In economies losing population, like Cleveland, Detroit, and Saint Louis, there remains substantial transportation infrastructure relative to local employment levels. In such cases, basic economic theory suggests that adding further transportation infrastructure will do little to increase local levels of productivity. Put simply, when transportation is not the problem, transportation cannot be the solution.

By contrast, added or improved transportation infrastructure in isolated, fast growing, and/or congested places can meaningfully affect local economic performance since it can increase access to economic opportunities for people and firms, thereby correcting for the imbalance between the relatively low capital and relatively high employment in such places (Glaeser & Kohlhase, 2004; Cheshire et al., 2014). While perhaps self-evident, when inadequate transportation inhibits economic activity, transportation investments can meaningfully affect regional economic productivity.

2.2.3 The Costs of Congestion on Economic Performance

As noted at the outset, because it slows travel speeds and decreases travel time reliability, traffic congestion is widely assumed to exact a toll on the performance of regional economies. According to the Texas Transportation Institute, traffic congestion imposed a $160 billion drag on the

U.S. economy in 2014, or around 0.9 percent of total gross domestic product (GDP) (Lomax et al., 2015). Previously, some have estimated traffic congestion to generate a cost as high as 2 to 3 percent of GDP per annum (Cervero, 1988). Furthermore, the cost to the economy from traffic congestion is believed to have increased over time. According to Schrank, Lomax, and Turner (2010), the cost of time delay to the U.S. economy increased from $24 billion in 1982 to $115 billion in 2009 (in 2009$).

These estimates typically measure what Sweet (2011) refers to as the first-order impact of traffic congestion. First-order effects refer to the immediate costs imposed to road users by time delay generated on transportation networks. There are typically two types of first-order costs: (a) nonproductive travel delay and (b) unreliable travel times. Beyond challenges in defining the value of time, the true cost of congestion, as seen through such a lens, is difficult to determine since it is not clear whether time spent in traffic is "unproductive," and therefore represents some form of opportunity cost (Sweet, 2011).

Sweet (2011) also identifies second-order congestion effects, which are the primary concern of the analysis reported here. Second-order effects refer to longer-term costs to economic productivity and growth that are induced by traffic congestion. If the diseconomies of scale (the costs of crowding) to which congestion gives rise increase to the extent that they outweigh the economies of scale from agglomeration (the benefits of crowding) – productivity declines and economic activity will tend to relocate to other parts of a region, or perhaps to other regions. Indeed, limited evidence does suggest that traffic congestion is a drag on employment and productivity growth across metropolitan regions (Hymel, 2009; Sweet, 2014).

In general, studies of the economic effects of traffic congestion are both few in number and vary widely in the scale of investigation, the measures of congestion and economic performance used, and the methodological approaches taken. This variation renders it difficult to compare results across studies in order to draw definitive conclusions about the effect of traffic congestion on economic performance.

The effect of congestion on economic outcomes has mostly been examined at two geographic scales. Some studies focus on the net effect of traffic congestion on economic performance across a range of cities and metropolitan economies (Hymel, 2009; Boarnet, 1997; Fields, Hartgen, Moore, & Poole Jr., 2009; Sweet, 2014a), while others examine the impact of traffic congestion on economic outcomes within regional economies (Graham, 2007; Sweet, 2014a).

Measuring roadway congestion has been an important part of transportation planning and engineering since the early years of the profession, and as federal, state, and regional oversight of transportation systems has evolved, accurate measures of road performance have become a critical part of evaluation, planning, and finance (Boarnet, Kim, & Parkany, 1998; Lomax et al., 1997). While measures of congestion across studies converge on the idea that traffic congestion increases travel time for road users compared to free-flowing driving conditions, individual indicators differ from study to study. Historically, such variation existed because different transportation agencies used different measures and methodologies to record local network data, while others maintained no information pertaining to local road networks at all (Boarnet et al., 1998). The absence of standard indices makes it difficult to compare individual studies and to test the net effect of congestion across a range of regions and times, without relying on crude proxies for congestion (Boarnet et al., 1998; Bartik, 1991). Encouragingly, new data sources, such as the Texas Transportation Institute's Urban Mobility Report, have made it possible to compare congestion across regions and to employ consistent measures across studies (see for example Hymel, 2009; Sweet, 2014).

As noted above, measures of economic performance in traffic congestion studies also differ greatly. In some cases, scholars seek to quantify the value of time delay, while others focus on employment growth, changes in productivity, or the performance and/or location of particular industries or by individual firms (Hymel, 2009; Sweet, 2011, 2014a; Boarnet, 1997; Graham, 2007; Fernald, 1999; Stopher, 2004; Weisbrod & Treyz, 2004). In addition to the variation in these measures, statistical modeling challenges are another reason for the lack of consensus in this field. The problem of "endogeneity" is the major statistical modeling constraint faced by scholars. Ultimately, traffic congestion is a product of social and economic activity, where the most congested regions are frequently the most economically vibrant. As a local economy expands, (whether through employment, output, or population growth), new trips are generated, which gives rise to traffic congestion. But just as economic growth causes traffic congestion, traffic congestion can in turn impede economic growth. To this extent, the two factors – economic activity and traffic – are highly correlated with, and determined in part by, one another, such that determining the direction of causation between the two variables has proved challenging (Hymel, 2009; Sweet, 2014). Given this unavoidable analytical conundrum, the different approaches employed to overcoming this challenge have, unfortunately, generated considerable variation in the findings across studies.

2.3 Behavioral Approaches: Coping with Congestion

A limited subset of research on congestion emphasizes not just costs, but possible responses to those costs, as experienced by transportation system users. This literature is largely focused on individuals and households rather than firms, but is important for suggesting that a phenomenon such as congestion need not generate particular, or even similar, behavioral responses. Rather, traffic congestion likely results in a multiplicity of responses all with differing effects on individuals, households, and general welfare. Broadly, this research conceptualizes responses to congestion quite humanistically as "coping." Rather than being simply a psychological response to distress, however coping with congestion encompasses a broad range of short- and long-term strategies that individuals, households, and businesses may employ to minimize the effects of congestion on their lives and wellbeing. A significant portion of the conceptual work on coping with congestion was developed by Salomon and Mokhtarian (1997), and is discussed below. Empirical studies examining tradeoffs among strategies are more limited, but suggest that a wide range of demographic and geographic factors help shape how congestion affects individuals, households, employees, and firms.

2.3.1 Salomon and Mokhtarian: Coping with Congestion

Salomon and Mokhtarian introduce the concept of "coping with congestion" (Salomon & Mokhtarian, 1997), examining multiple strategies that individuals and households may employ to cope with congestion during daily commutes. Delineating a range of sixteen strategies that travelers may employ when responding to congestion, they emphasize that the effects of congestion mitigation policies are difficult to predict inasmuch as (1) travelers may differentially respond to existing and future congestion levels, (2) travelers differentially perceive congestion costs and the benefits of mitigation policies, and (3) costs and benefits from different strategies will be distributed unevenly across individuals, their households, and society. They discuss the wide diversity of strategies by which individuals and households might respond to congestion, and how a range of effects, not only monetary but also time, stress, inconvenience, and other effects accrue benefits and costs to commuters, their households, and others generally.

Overall, the "coping with congestion" framework underscores that traffic congestion's costs are likely to be understood very differently across individuals and thus result in very different outcomes. A traveler may cope with congestion simply by passively "accommodating" it, leaving more time for travel and compound the total congestion problem. They may also engage in proactive solutions such as changing travel mode, if policies facilitate those changes, or even change their employment status. Importantly, many of these individual and household-level responses to congestion may have firm-based analogues, which we describe in greater detail in Section 2.4.

2.3.2 Empirical Investigations of Congestion and Accessibility

The conceptual framework established by Salomon and Mokhtarian has been followed up with only a limited amount of empirical research. The research completed, however, helps demonstrate the relative importance to individuals of the various strategies they proposed, as well as the determinants of the choice of a particular strategy relative to others. Salomon, Mokhtarian, and their collaborators have done most of this empirical exploration themselves. Specifically, they have examined the relative likelihoods that commuters will employ any of the sixteen strategies first described in 1997, or bundles of those strategies, by modelling potential congestion responses collected in a 1998 survey of Bay Area commuters (Cao & Mokhtarian, 2005; Choo & Mokhtarian, 2007). The models suggest the likelihood, which varies significantly across strategies, of a given strategy to being chosen. In addition, they find that strategy choice is dependent on a wide range of individual-level factors including travel characteristics but also attitudes, personality, and lifestyle.

Mondschein and Taylor (2016) extend the coping literature by exploring the relationship between trip frequency, mode choice, and location. They find that responses to congestion vary significantly by location across an urban area, specifically in terms of access to destinations. Using congestion and travel survey data from the Southern California region, they find that in areas with low access to destinations, increasing congestion is associated with a reduction in total activity participation (which they measure in terms of tripmaking), while in areas with relatively high access to destinations, increasing traffic congestion does not significantly affect activity participation. However, it does reduce the likelihood of driving and increase the likelihood of walking for a given trip. The study emphasizes that responses to congestion are likely highly location dependent in terms of local land use and the availability of alternatives to being stuck in traffic.

2.4 Conclusion: Conceptualizing firm behavior as "coping?"

As this chapter has demonstrated, the relationship between traffic congestion and economic performance is complex in nature. Despite the great interest in understanding how road network delay shapes the fortunes of regional economies, the empirical literature provides, at best, an ambiguous insight into this issue. In short, while theory and intuition would predict that traffic congestion should impede economic performance, there is not a large body of research that demonstrates that traffic congestion meaningfully hinders local economies in the developed world. As we describe above, methodological challenges are a big part of the problem in understanding the relationship between congestion and economic performance. It has not only been difficult to find a consistent and reliable measure of traffic congestion historically, but since traffic congestion is one of many closely related factors that affect access and economic performance, measuring the net effect of congestion has been an elusive task for researchers.

Beyond these methodological challenges, the weak evidence of a relationship between traffic congestion and economic performance can perhaps be explained by the actions of firms. To refresh, firms of basic industries show a propensity to locate in close proximity to one another. Ultimately, such proximity enhances firm accessibility to industry-specific workers, suppliers, and information. The Bay Area is well known for its traffic congestion. However, a firm seeking to access the high-tech industry eco-system would be better placed to do this on the crowded streets of San Jose or San Francisco than on the high-speed, free-flowing roads of rural Iowa. While this statement suggests that congestion is a price that an IT firm has to pay to access the Bay Area high-tech industry complex, it does little to help us understand how much more productive a firm might be in the Bay Area absent congestion.

We can confidently assume that the costs of traffic congestion in the San Francisco Bay Area do not fully offset the benefits that many technology industry firms yield from clustering in the region. Otherwise, we would see an exodus of such firms from the Bay Area to less congested venues; an exodus that is not in evidence.[2] In other words, if the benefits from clustering did not offset the costs of congestion, technology industry firms would migrate elsewhere. That said, lowering congestion costs, all things being equal, would clearly benefit tech industry firms and their employees. But the economic benefits of lowering the costs of production are by no means limited to reducing congestion costs; lower land costs, taxes, utilities, or input costs also benefits firms and industries. In cities like San Francisco, Los Angeles, and New York, many firms leave the region due to the high costs of land. These cities are simply too costly for the firms of many industries. For example, there is little benefit today for a firm in the textiles industry to locate in Boston. A Boston location, with its high land and labor costs, would cause a textiles firm to pay a premium to access inputs (such as high-skill labor) upon which it does not rely. In the case of the Bay Area, congestion represents one of many costs a firm must absorb to access networks of technology industry suppliers, a labor market deep in electrical engineering and computer science skills, venture capital, and the like. The absorption of congestion costs in order to locate in the Bay Area, however, does not mean that firms cannot undertake efforts to mitigate the effects of congestion.

In the chapters that follow, we turn to empirical examinations of the relationship between traffic congestion and firm-to-firm accessibility in the San Francisco Bay Area. First, we will seek to understand the major determinants of access among firms of the same industry, with a particular focus on the roles placed by traffic congestion and such as firm-to-firm proximity. Following this, we then turn to an analysis of whether traffic congestion inhibits the creation of new firms within the Bay Area regional economy. It is to these analyses that we now turn.

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[2] While overtime the assembly of most technology industry hardware has migrated from Silicon Valley to other, lower cost regions, particularly in the developing world, there is scant evidence that these shifts are centrally, or even partially, related to the costs of traffic congestion, given that higher-skill, higher-way tech industry employment has grown in the Bay Area over time.

Chapter 3: Congestion in the Bay Area: Speed, Proximity, and Access

3.1 Introduction

As noted earlier, the San Francisco-Oakland urbanized area has achieved traffic congestion levels that place it near the top of national metropolitan rankings (Lomax et al., 2015). These rankings, however, emphasize network-focused differences between peak-hour and free-flow speeds, with delay estimates on each link aggregated to an overall valuation of time or dollars lost due to traffic congestion. As discussed in Chapter 2, such measures are of mobility (in this case vehicle volumes and speeds) and not of access (i.e. the activities and interactions enabled by travel). The former treats travel as an end in itself, while the latter treats travel as a means to the end of facilitated place-based interactions that people and firms value (Grengs, 2010; Kawabata and Shen, 2006; Shen, 2001; Wachs and Kumagai, 1973). In an accessibility framework, the utility of a grocery shopping trip lies in the ability to purchase and transport home desired foodstuffs at reasonable time and monetary costs, and is only indirectly related to the speed of vehicular travel between a home, the grocery store, and back.

This distinction between mobility and accessibility is important because travel speed is but one contributing component of the latter. The capacity to traverse space is a function of speed, but also of knowledge about destinations, modal options, possible routes, the monetary costs of travel, and risk and uncertainty (Chorus et al., 2006; Taylor & Norton, 2010; Carrion & Levinson, 2012). And the capacity to traverse space is, in turn, just one dimension of access, the others being the diversity and proximity of destinations. As noted previously, while higher travel speeds and a greater density of nearby destinations can both contribute to higher accessibility levels, the two factors oftentimes work at cross purposes. Areas that enjoy high travel speeds often exhibit low density and few nearby destinations, while dense hubs of activity often feature clogged roadways and slow travel. Importantly, these countervailing features of accessibility vary significantly across neighborhoods and districts, which is not evident in regional congestion measures, such as those published by the Texas Transportation Institute and Inrix. Thus, to understand how the relationships between speed and proximity affect access, we must examine them at a local scale.

The potentially complex interplay between density and speed means that gaining a functional understanding of accessibility is necessarily an empirical undertaking. It is simply not possible to say *a priori* how the relative levels of accessibility in, say, a neighborhood with easy highway access and smooth-flowing arterials will compare to those in a dense neighborhood with tightly gridded streets and heavy peak-hour congestion. Despite accessibility's conceptual elegance, its empirical investigation is just beginning to catch up to its theoretical standing. Valuable empirical efforts have recently included comparisons of inter-regional accessibility, examining the interplay of region-level attributes of density, speed, and access (Grengs, 2010; Levine et al., 2012), as well as detailed assessments of vehicular, transit, and non-motorized accessibility at fine-grained neighborhood levels (Owen & Levinson, 2015; Levinson, 2013). There has been little attention paid, however, to the potentially complex interplay of speed and density at the neighborhood or district level.

It is at this sub-regional level where an informed understanding of the relative influences of speed and density in helping people access destinations can have the greatest implications for policy and planning, particularly as such an understanding relates to our treatment of traffic congestion. Assuming accessibility to be largely a function of speed will almost certainly lead us to inappropriately prioritize congestion reduction at the expense of land use considerations that may be as or more effective in improving accessibility. Likewise, though likely a less common occurrence, prioritizing proximity and density in places where speed most importantly contributes to accessibility could prove problematic as well. Finally, we should expect that these relative contributions of speed and proximity vary not only among metropolitan areas, but even more importantly within them as well.

We thus report in this chapter on a data-driven assessment of the relationships among speed, proximity, and accessibility for the San Francisco Bay Area. Specifically, we analyze the three-way relationships among these variables for the nine-county region defined by the (San Francisco Bay Area) Metropolitan Transportation Commission as a whole, as well as how these relationships vary across the region's communities. Our goal with this analysis is to better inform how travel speeds (or lack thereof) are understood and responded to by engineers, planners, and public officials, and how trade-offs between speed and development density may be evaluated in different kinds of communities across the Bay Area.

To tip our hand, we find broadly that proximity matters more than speed in explaining job access, both overall and for specific industries. However, these relationships vary significantly across the region's counties and neighborhoods. Neighborhoods in some counties -- such as San Mateo and Santa Clara – are relatively dependent on speed for their accessibility, while neighborhoods across the region benefit more from dense concentrations of nearby development and employment, despite the chronic heavy traffic that such concentrations sometimes bring.

3.2 Data and Methods

Given our hypothesis that the effects of traffic congestion are most meaningfully measured through their effects on access to destinations, we examine these effects in the San Francisco Bay Area using destination and mobility data for the nine counties: Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma. Our data come from two primary sources: traffic analysis zone-to-traffic analysis zone (TAZ) distance and travel time data from the Metropolitan Transportation Commission (MTC), and employment at businesses throughout the region derived from the National Establishment Time-Series (NETS) database. NETS is a proprietary micro-dataset assembled by Walls and Associates and comprised of Duns Market Information business directory data

(DMI). NETS has tracked the "birth" and "death" of each establishment in the U.S. since 1990. Over the life of an establishment, the dataset contains records on the employment level and street address of each establishment for each year, so that births, deaths, and relocations can be tracked.

For our focus baseline employment year of 2009, we derived geographic coordinates for every establishment listed in the targeted Bay Area counties. We obtained these geographic coordinates through the use of two different geocoding application programming interfaces (APIs), both accessed from within the R statistical programming language. We first used an API provided by the Data Science Toolkit website (Data Science Toolkit, 2015), which makes use of Open Street Maps and Census data to translate street addresses into coordinates. For firms with complete address data that did not return valid coordinates through the Data Science Toolkit API, we attempted to re-code them using Google's proprietary mapping API, accessed through the "ggmap" package in the R statistical software language (Kahle and Wickham, 2013). The final set of geocoded business records were then linked to the unique traffic analysis zones in which they fall. With each business associated with a traffic analysis zone, we then calculated the total employment within each zone.

3.2.1 Focus on Peak Speeds

Having a complete set of TAZs for our region of study, we calculated a number of mobility-related measures that figure centrally into the study of accessibility's determinants. First, using matrices of 2010 zone-to-zone road network distances and automobile travel times from MTC, we calculated the average speeds of motorists from each TAZ to all other TAZs within a given network-derived distance, which gave us a basic set of speed measures for the entire region. The speed measures average both inbound and outbound speeds from a TAZ to its neighbor TAZs during the morning peak period. We emphasize peak speeds because we argue that most, though not all, employees and firms are likely to make their choices about where to live, where to work, and where to set up shop based on peak commute hour travel times.

3.2.2 *Bringing in Accessibility*

Next, we calculated the total level of employment located within the same range of network distance threshold-based neighborhoods, giving us a basic measure of destination proximity. Figure 3.1 shows the distribution of jobs throughout the region, drawing from the NETS data. Finally, we combined speed and proximity into a single "gravity" weighted accessibility score for all traffic analysis zones. The accessibility models we used were all of the following form, as it appears frequently in the accessibility literature (Handy & Niemeier, 1997; Grengs et al., 2010; Geurs & Van Wee, 2004):

$$A_i = \sum_j E_j \ e^{-\beta T_{ij}}$$

In this equation, A_i represents the total accessibility for zone i, E_j represents the total amount of employment in each destination zone j, and T_{ij} represents the morning peak-hour travel time in minutes from zone i to zone j. Finally, the parameter $e^{-\beta}$ has the effect of determining how much travel impedance matters in weighting a zone's accessibility contribution; larger values mean that even relatively short travel times will greatly devalue the accessibility benefit of neighboring destinations, while smaller values of mean that accessibility scores will give greater weight to a wider swath of destinations. In terms of labor markets, relatively lower skill, spatially dispersed jobs – like fast food worker – would tend to have higher values (i.e. more friction of distance), while higher skill, scarcer jobs – like cardiologist – would tend to have lower $e^{-\beta}$ values (i.e. lower friction of distance); this is because workers are less likely to commute long distances to relatively low paying, spatially ubiquitous jobs, but more likely to be willing to endure long commutes to much rarer and higher paying work. For the purposes of our analysis, which emphasizes access across multiple industrial sectors, we apply a common $e^{-\beta}$ value to represent the friction of distance between residents and jobs across the entire labor market.

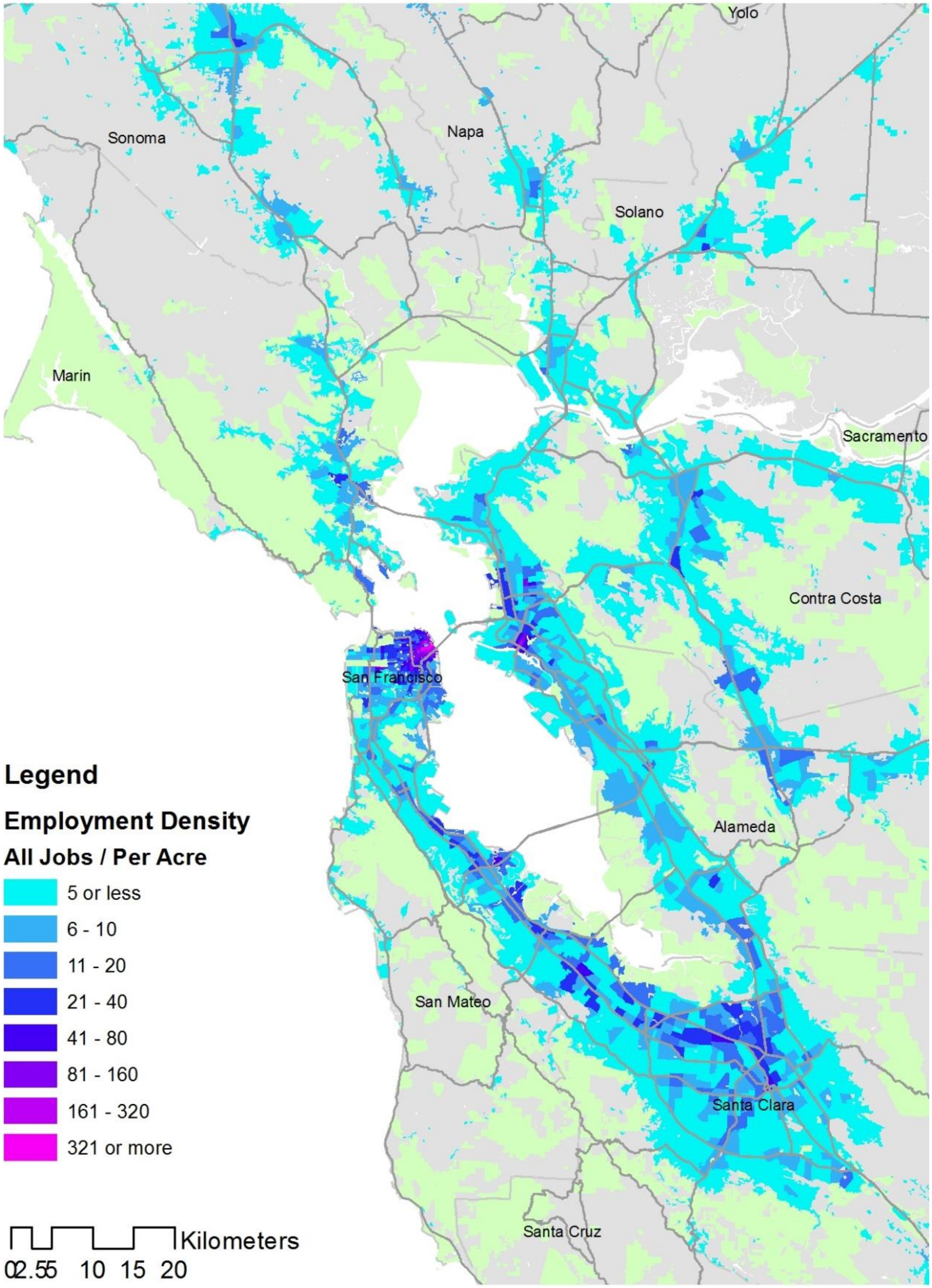


Figure 3.1 Employment Density, Jobs in All Sectors per Acre, 2009

In assessing relationships among the speed, proximity, and accessibility variables just discussed, we are presented with a vast number of potential parameter combinations; we must choose a specific time impedance value for the gravity-based accessibility function, and we must choose network distance cutoff thresholds for both speed and proximity calculations. We address this problem of myriad modeling permutations in two primary ways. First, we selected our gravity model parameter value by drawing from the accessibility literature. Such model parameter values typically range from approximately 0.05 to 0.5, with many values close to 0.2 (Handy & Niemeier, 1997; Grengs et al., 2010; Sweet, 2014). Using this 0.2 value for our models, we then identified the tightest empirical association (as determined by the goodness of fit of linear models) with speed and job proximity threshold values of 10 kilometers, motivating our choice for these threshold values for use in our analysis. Second, we tested the robustness of our findings by running descriptive models for a wide range of parameter combinations. While we focus our presentation on a single representative set of parameters, the same broad relationships reported here hold for a wide range of the parameter value combinations we tested. Table 3.1 provides a summary of the accessibility, proximity, and speed statistics associated with our selected model parameters.

Table 3.1 Summary Values for Accessibility, Proximity, and Speed Variables, Measured at the TAZ Level

Statistic	Mean	Standard Deviation	Minimum	Median	Maximum
Average Peak-Hour Speed (km/hr; distance threshold = 10 km)	37.4	4.1	25.2	38.1	57.8
Employment Proximity Count (distance threshold = 10 km)	199,069	187,350	220	134,648	715,271
Employment Accessibility Index (decay parameter = 0.2)	38,361	27,256	47	32,965	138,989

Note: All proximity and accessibility measures are calculated for the full set of 1,454 TAZs in the Bay Area region.

3.4 Findings

3.4.1 Region-wide Patterns

The complex inter-relationships among speed, proximity, and accessibility are demonstrated in the paired bivariate comparisons shown in Figure 3.2. These graphs present two clear and sharply contrasting pictures, with employment accessibility very closely linked to employment proximity on the one hand, and with higher speeds largely *inversely* related to employment accessibility on the other. How can this be? The answer is that these are actual data for the Bay Area and not hypothesized relationships. While, all things equal, higher speeds will of course get one to more destinations in a given amount of time, all things are rarely equal. Higher peak hour speeds, at least in the Bay Area, tend to be in outlying areas where densities are low and jobs sparse (see the upper-left panel in Figure 3.3). Conversely, jobs tend to be clustered in places where densities are high and traffic congestion chronic. Overall, more jobs can be reached in a given amount of time via the crowded streets of San Francisco and Oakland than on the faster moving freeways and arterials on the fringes of the metropolitan area. Put in general terms: as speeds increase, the accessibility benefits of lower travel time impedances are more than canceled out by an associated lack of nearby destinations.

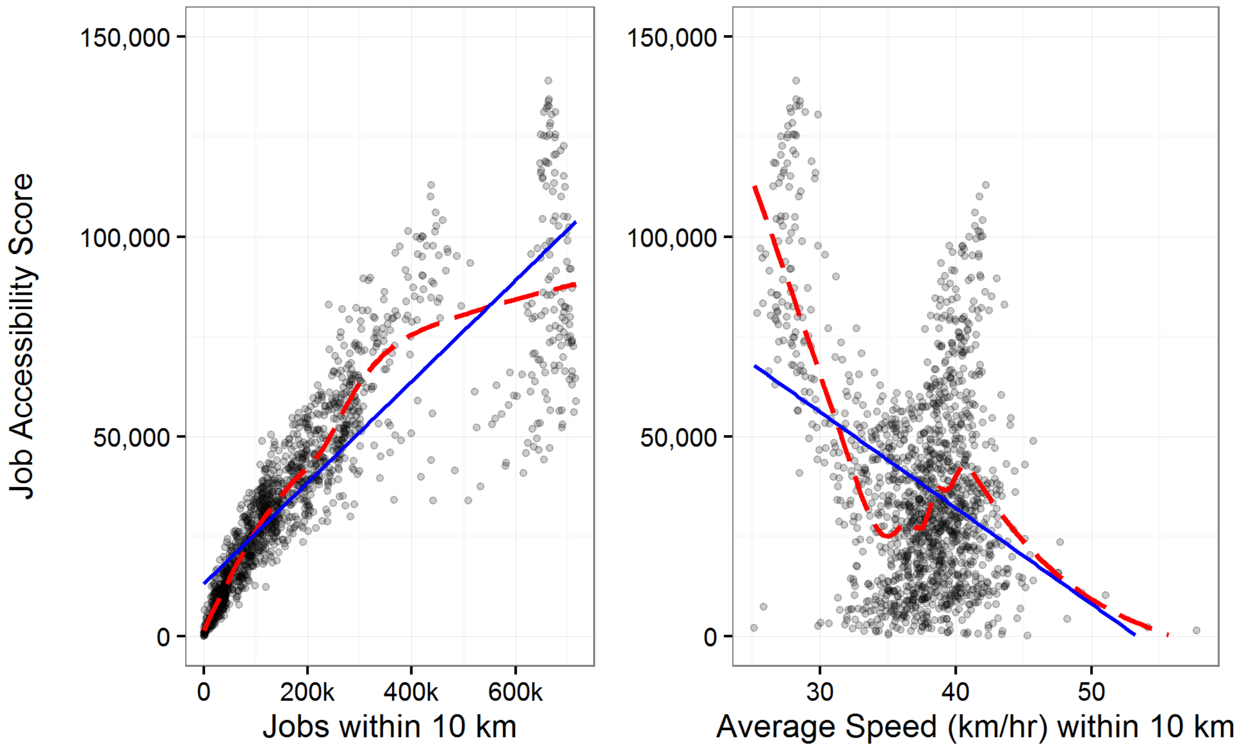
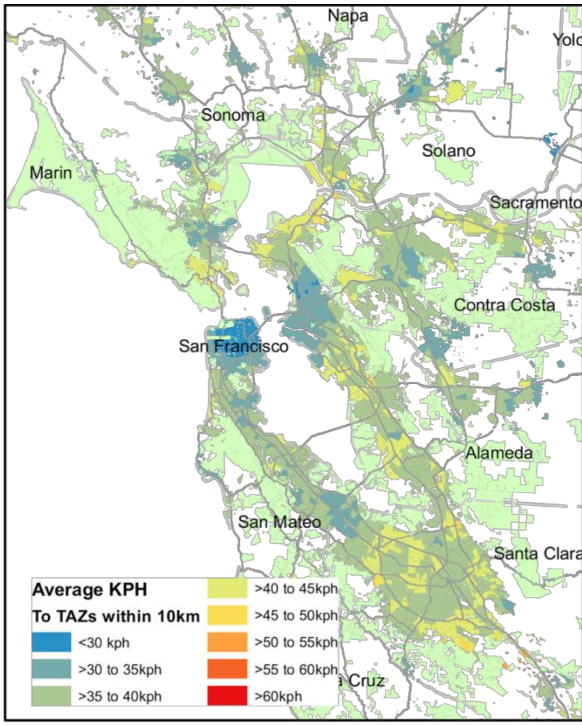


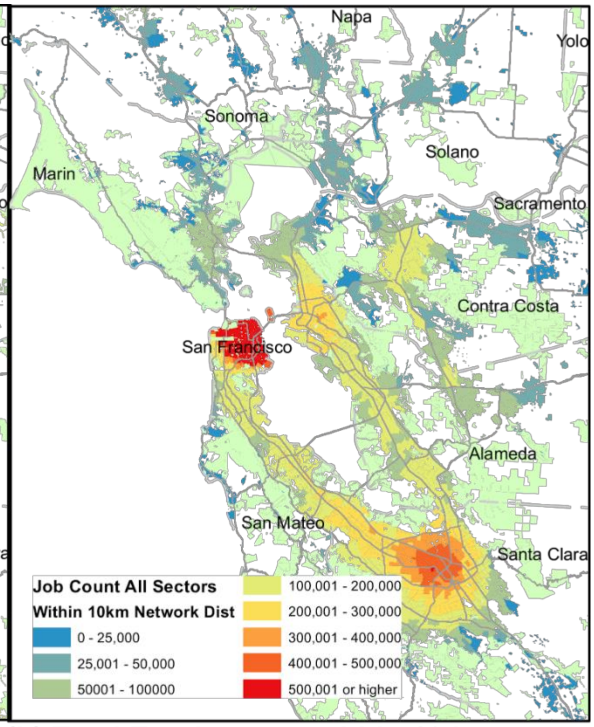
Figure 3.2 Bivariate Graphs Linking Employment Accessibility to Employment Proximity (left) and Speed (right)

This three-way link among accessibility and its two principal components is made clearer by examining all three variables mapped and plotted against one another in Figure 3.3. Here, we see TAZ-level maps of speed (top left corner), proximity (top right corner), and accessibility (bottom left corner) all displayed such that higher values take warmer colors and lower values take cooler colors. Several observations jump out from these maps. As discussed above, speed and proximity in the Bay Area display a strong, negative relationship, with their respective coloration patterns displaying as rough inverses of one another. Also, corroborating the plots in Figure 3.2, the coloration of speed appears as an inverted version of the accessibility color pattern, while the coloration of proximity is very tightly aligned with that of accessibility. These qualitative visual observations are bolstered by the scatterplot in the lower right panel in Figure 3.3. Here, we again see a distinctly negative relationship between proximity (running horizontally) and speed (running vertically). This plot also displays the accessibility values of traffic analysis zones of different speeds and employment proximity values. Again, we see a very clear trend of accessibility values increasing from left to right on the graph (indicating a strong proximity-accessibility relationship), but with little increase from bottom to top (indicating a weak relationship between travel speeds and accessibility).

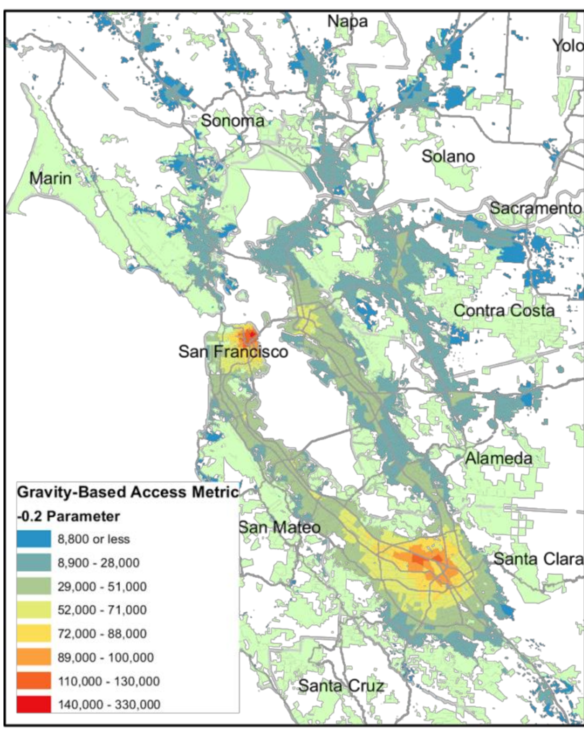
To more directly evaluate the patterns depicted in Figure 3.3, we specified three ordinary least squares (OLS) regression models, accounting for accessibility in terms of speed alone, proximity alone, and a combination of the two. The results of these models are shown in Table 3.2. To better facilitate comparison among the models, each variable has been scaled, such that the standard deviation is one and the mean is zero. Model 1 shows that, in the absence of other predictors, a one standard deviation increase in speed corresponds to a 0.36 standard deviation *decrease* in employment accessibility, whereas Model 2 shows that by itself a one standard deviation increase in proximity to jobs corresponds to a 0.87 standard deviation *increase* in accessibility. When both independent variables are included in the same model, proximity maintains its strength as a predictor of accessibility. After accounting for proximity, the sign for speed switches – speed now becomes a positive predictor of accessibility – but it is still not a powerful predictor and does relatively little to increase the explanatory power of the model. Why does the sign for the effect of speed on job accessibility switch from negative to positive in the combined model? This is because proximity is already accounting for most of the variance in job accessibility, so that we can think of the measure of speed in this model as the marginal effect on job accessibility after controlling for the effects of proximity. So while proximity does the lion's share of the work in explaining job access, once you hold the level of proximity constant, it is of course better to travel faster rather than slower in reaching jobs.



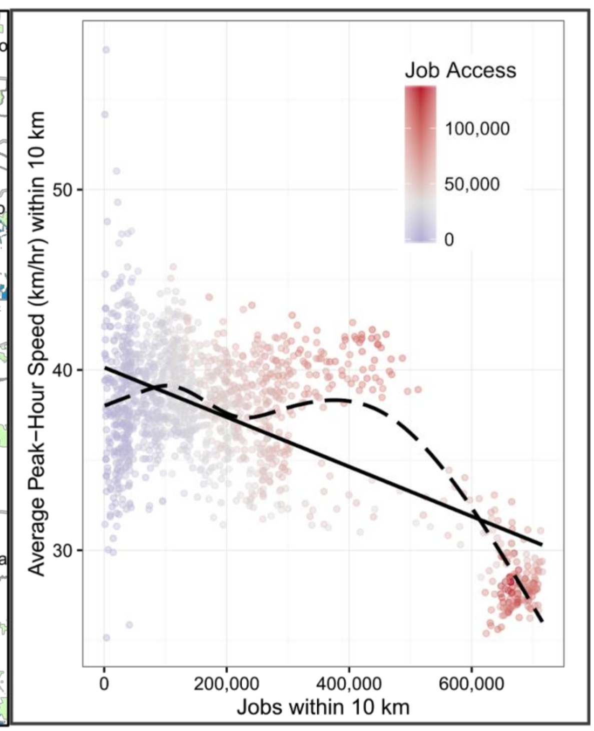
(a) Average Peak Period Speed to TAZs within 10 km (network distance)



(b) Total Employment within 10 km (network distance)



(c) Exponentially Weighted Access to Jobs (-0.2 parameter)



(d) Speed (vertical axis) vs. Proximity (horizontal axis), Colored by Job Access

Figure 3.3 Speed, Employment Proximity, and Employment Accessibility Plotted Against Each Other, Cartographically and by Color-Coded Scatterplot

Table 3.2 OLS Employment Accessibility Model Results

	Dependent variable: Employment Accessibility Score, Scaled		
	(1)	(2)	(3)
Peak-Hour Speed, Scaled	-0.361***		0.306***
	(0.024)		(0.015)
Employment Proximity, Scaled		0.871***	1.062***
		(0.015)	(0.015)
Constant	0.001	-0.000	0.0002
	(0.024)	(0.013)	(0.011)
Observations	1,453	1,454	1,453
R^2	0.131	0.758	0.814
(Standard errors in parentheses)	*p<0.1; **p<0.05; ***p<0.01		

As all variables here are scaled, they can be directly compared to one another, and in Model 3 we see that a one standard deviation change in proximity has ten times the effect on accessibility as does a similar change in speed. Likewise, looking at the different models' respective R^2 values, we see that adding proximity to the speed model results in a very large jump in predictive success, with the percentage of variance explained increasing from 13.1 percent to 81.4 percent. In comparison, the proximity-alone model (Model 2) accounts for 75.8 percent of the variance in accessibility, nearly as much as the model that includes *both* speed and proximity as predictors. From these models, we see strong evidence that proximity to employment is largely what drives employment accessibility in the Bay Area.

3.4.2 Subregional Variations in Accessibility

While the relative contributions of speed and proximity to regional employment accessibility in the Bay Area are clear, this does not necessarily mean that the predominant role of proximity holds in all parts of the region. Perhaps increasing job density is the primary predictor of increasing employment access in some areas, while speed plays a greater role in access to jobs in others. Relatedly, perhaps *within* a given area (either high- or low-accessibility) where job proximity is roughly similar, the effect of speed on accessibility will be positive (and more in line with the intuitions of the average traveler and elected official), as suggested by Model 3 above. To test these questions we assign our traffic analysis zone-based data to the nine different counties that constitute the Bay Area in a multilevel model, yielding an average of 162 zones per county.

Figures 3.4 and 3.5 show how the relationships among our three variables of interest vary within given communities. We reproduce the scatterplots shown in Figure 3.2, this time repeating each plot nine times, with each repeated plot highlighting a single county. Focusing first on Figure 3.4, we see that, while the overall regional relationship between speed and accessibility is clearly negative, this relationship is more complicated when viewed at the county level. In San Francisco and to a lesser extent Alameda County, there remains a clear negative correspondence between speed and accessibility, while in most other counties there appears to be little pairwise correlation, and in Santa Clara this is actually a substantial positive correspondence between the two variables. Turning to the proximity-accessibility relationships depicted in Figure 3.5, we see much less county-level variation; while the slope of the relationship varies somewhat from county to county, each of the nine counties shows a similarly substantial positive link between job proximity and job accessibility.

While the patterns depicted in Figures 3.4 and 3.5 are interesting and suggestive, they do not lend themselves to direct inferences about the combined effects of speed and proximity at both the between-county and within-county levels. To establish a more rigorous understanding of these intra- and inter-county relationships, we specify a set of three hierarchical (or multilevel) linear models corresponding to the models shown in Table 3.2. To directly model the difference between intra- and inter-community relationships, we follow Raudenbush and Bryk (2002) by applying a technique of “group mean centering.” Using this technique, we calculate the mean value of the speed and proximity variables within each county. We then create a “centered” variable by subtracting the county mean from each traffic analysis zone within the given county, allowing us to decompose the effects on accessibility of differences between counties and differences within counties. As with the prior set of models, we then scale these within- and between-county variables by centering them around zero and dividing them by their standard deviation, allowing for a direct comparison of model coefficient sizes. We carried out this hierarchical modeling using the “lme4” package within the R statistical programming language (Gelman & Hill, 2007).

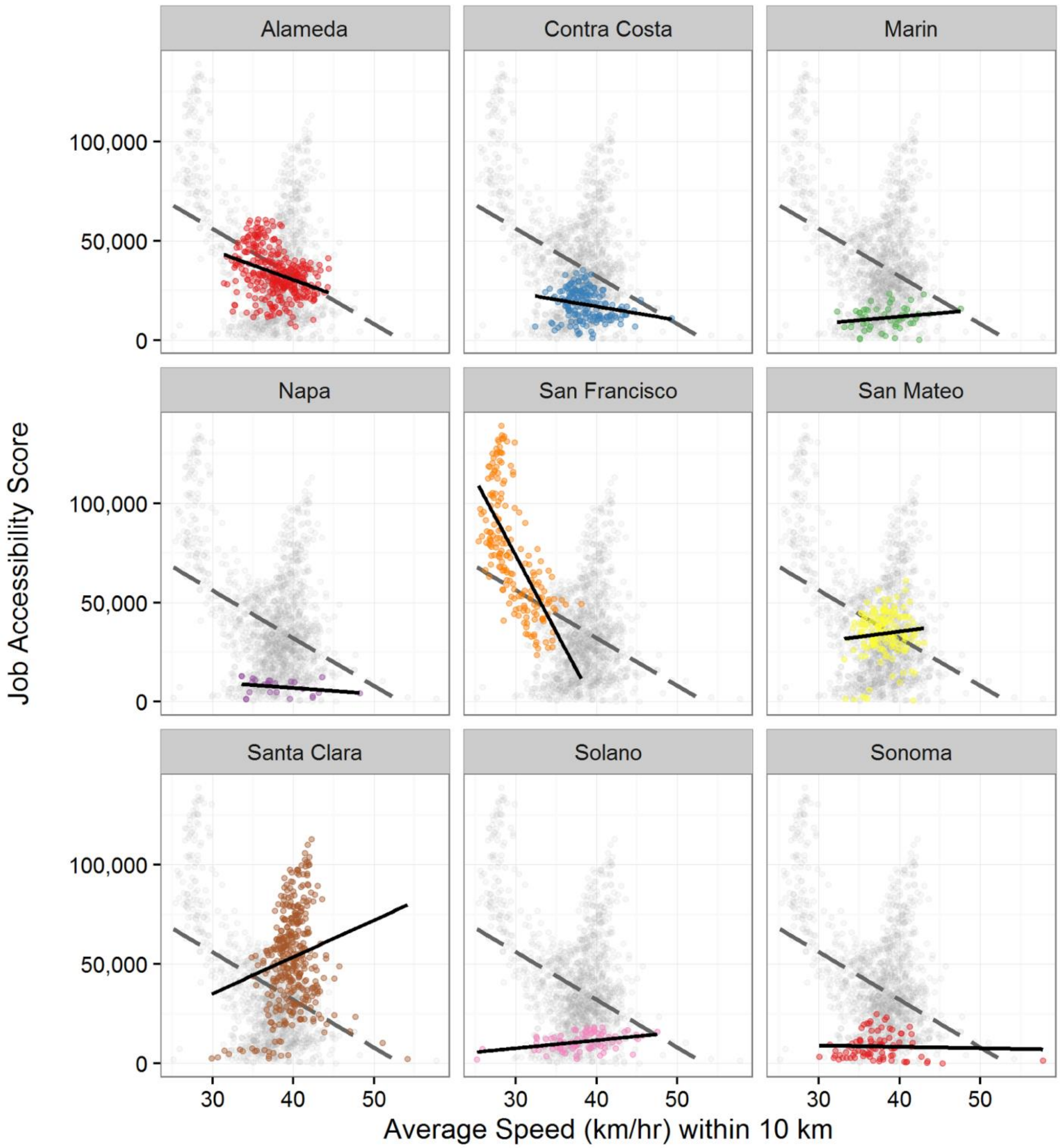


Figure 3.4 Region-Wide Relationship Between Speed and Accessibility (dashed line), Overlaid with County-Level Relationships (solid line)

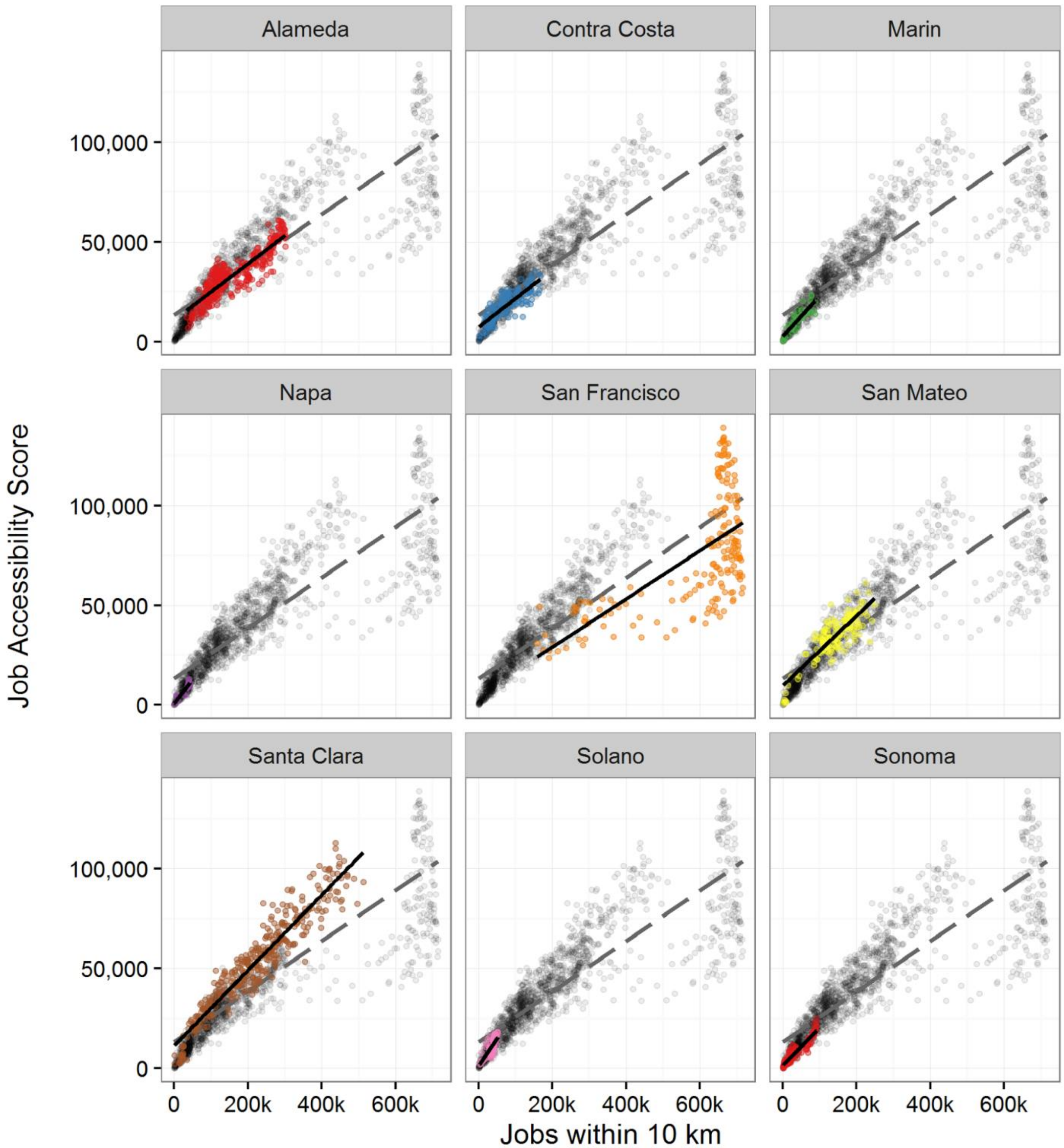


Figure 3.5 Region-Wide Relationship Between Proximity and Accessibility (dashed line), Overlaid with County-Level Relationships (solid line)

The results of this hierarchical modeling are depicted in Table 3.3 and Figure 3.6, with Table 3.3 displaying "fixed effects" that hold across the region as a whole, and Figure 3.6 displaying "mixed effects" that incorporate both regional fixed effects and county-specific "random effects." Looking first at the contextual effects of speed on accessibility (Model 1), we see that the accessibility score of a traffic analysis zone is strongly negatively predicted by that the average speed of that zone's parent county. Conversely, we see that within each county, differences in peak-hour driving speeds have little correspondence with accessibility. This corroborates the patterns shown Figure 3.4, as the slopes of intra-county speed are variable but generally flat.

Table 3.3 Hierarchical Linear Model Output for Relationships among Speed, Proximity, and Accessibility Variables: Fixed Effects

	Dependent variable: Employment Accessibility Score, Scaled		
	(1)	(2)	(3)
Scaled Peak-Hour Speed, County-Level Mean	-0.489*		0.281***
	(0.267)		(0.026)
Scaled Peak-Hour Speed, Within-County Difference from Mean	-0.078		0.003
	(0.092)		(0.067)
Scaled Proximity to Employment, County-Level Mean		0.795***	1.113***
		(0.053)	(0.028)
Scaled Proximity to Employment, Within-County Difference from Mean		0.504***	0.524***
		(0.030)	(0.046)
Constant	-0.384	-0.121	-0.017
	(0.241)	(0.098)	(0.075)
Observations	1,453	1,454	1,453
Log Likelihood	-1,319	-600	-487
Akaike Inf. Crit.	2,653	1,213.428	998
Bayesian Inf. Crit.	2,690	1,250.402	1,062

(Standard errors in parentheses) *p<0.1; **p<0.05; ***p<0.01

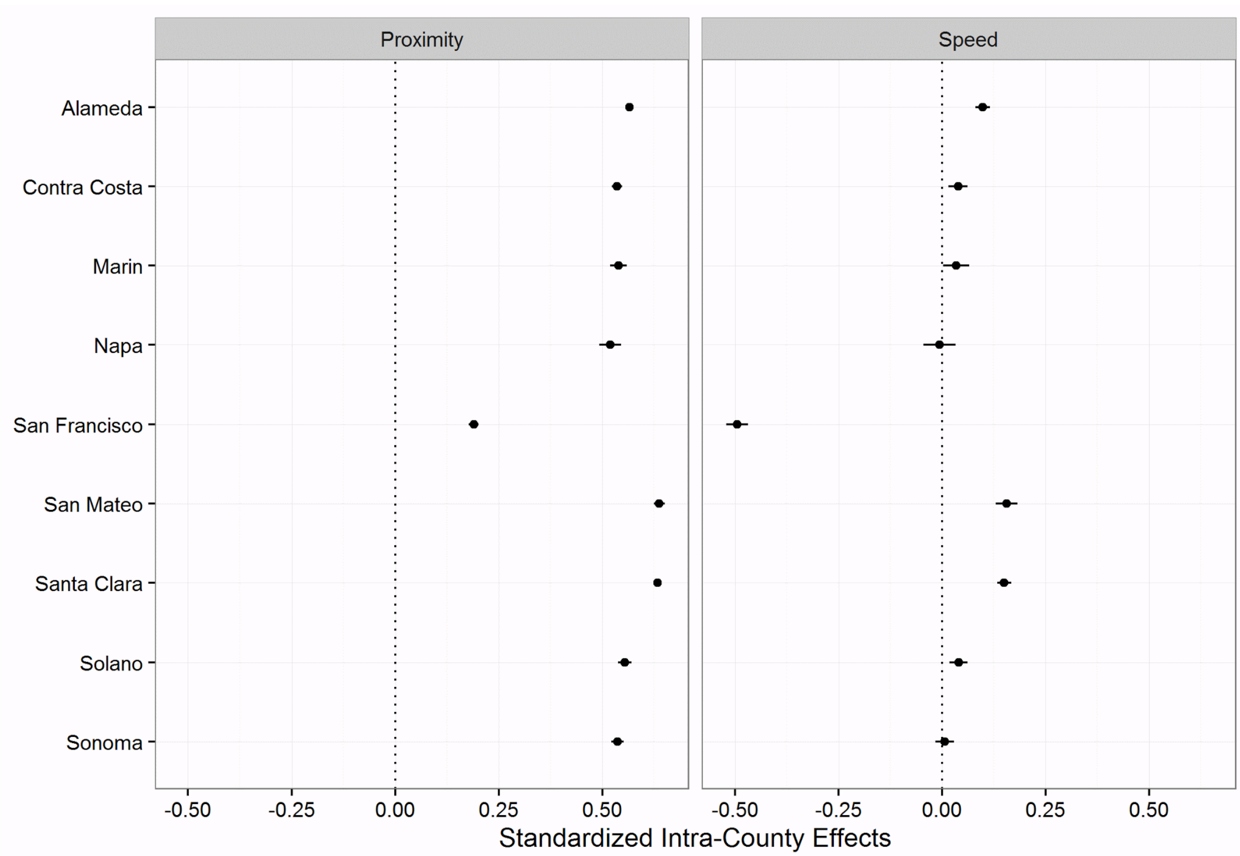


Figure 3.6 Modeled Effect Sizes of within-County Differences in Speed and Employment Proximity on Access

In Model 2 of Table 3.3, we see a parallel of the corresponding results in Table 3.2, and again a corroboration of the patterns shown in Figure 3.5; increases in job proximity are strongly linked to increases in job accessibility, with this link holding for both county-level average proximity and within-county differences in proximity, though the effect of the county-level averages is somewhat greater. Finally, Model 3 (just as with the corresponding model shown in Table 3.2) shows a flipped effect for speed. When accounting for proximity, increases in the average speed of a zone's parent county correspond to substantial increases in accessibility, while the effects of intra-county differences in speed remain insignificant. Still, as with the corresponding model in Table 3.2, proximity substantially outweighs speed in its effect on accessibility, both in terms of inter- and intra-county differences.

Turning to Figure 3.6, we see the specific county-level estimates of the effects of within-county variation in speed and proximity. These estimates (with standard errors represented by associated black lines), are generated by summing the fixed effects shown in Table 3.4 with deviations from these effects calculated separately for each county. Several interesting patterns emerge. Most notably, San Francisco is a major outlier in terms of both intra-county speed and proximity effects. In terms of proximity, while most counties do not deviate substantially from the fixed effect of 0.5, San Francisco shows a much weaker effect, with a one standard deviation increase in proximity yielding an increase in accessibility of only about 0.19 standard deviations. This result can be explained by referring back to the county-level scatterplots in Figure 3.5. While all the counties show similar slopes for proximity-accessibility fit lines, San Francisco's pattern of accessibility scores shows a distinctly looser correspondence. Specifically, at very high levels of job proximity (> 600,000 jobs within 10 km), San Francisco shows a wide range of accessibility scores. San Francisco is also an outlier with respect to speed; while again, most counties show speed effects similar to the null fixed effect, San Francisco shows a sharply negative relationship between intra-county differences in speed and accessibility, even after accounting for proximity. This, finding also corroborates patterns that can be seen from the scatterplots in Figure 3.4, as San Francisco is notable for the sharply negative slope in its relationship between speed and accessibility.

This counterintuitive combination of proximity and speed effects in San Francisco can be explained by the 10 kilometer scale at which we measure speed and proximity, in combination with the distinctly unique peninsular geography of the City and County of San Francisco. While the majority of traffic analysis zones in San Francisco are proximate to large concentrations of employment, and hence score highly in terms of number of jobs within 10 km, neighborhoods that are very near especially high-density employment centers score especially high on the accessibility scale. These same very-high-density clusters are likely also to contribute to especially slow travel speeds, however, even when measured over 10 km distances. This combination of factors explains both the weak correspondence with job proximity totals and the highly negative correspondence with speed.

The opposite set of effects can be seen, to a more muted degree, in San Mateo and Santa Clara Counties, which comprise the San Francisco Peninsula and Silicon Valley, respectively. In these counties, job proximity and travel speed both display positive and stronger than usual effects. Within these counties, it is both the case that having a greater number of jobs within 10 km disproportionately increases accessibility, as well as the case that experiencing greater travel speeds within 10 km disproportionately increases accessibility. This combination of effects is likely explained by the moderately high and relatively even patterns of job density in these counties; being more centralized within a broader swath of density corresponds to greater accessibility, as does having the ability to travel more speedily across these broader swaths of urbanization.

3.5 Interpretation

The findings presented here yield a number of important implications for transportation and land use decision makers, as well as for researchers. Most notably, the results confirm at the neighborhood level within the San Francisco Bay region what other researchers have found in a comparison among different regions (Levine et al., 2012): (1) there is a clear tradeoff between proximity to destinations and average vehicular travel speed, and (2) proximity does a great deal more work in accounting for neighborhood-level access to destinations than does speed. These relationships among speed, proximity, and accessibility are strong and fairly linear across the region as a whole. While it is clear that proximity is by far the primary predictor of accessibility at the neighborhood level across the region, the results presented here show interesting and important complexities with respect to the county-level context of average speed. Namely, looking at the pooled total of all neighborhoods in the region, county-level averages of proximity and speed are substantially stronger predictors of accessibility than are differences in proximity and speed measured within each county. These within-county effects also show important variation, though, with San Francisco showing a counter-intuitive combination of weak proximity effects and strongly negative speed effects, while the San Mateo and Santa Clara Counties show the opposite, with both speed and proximity being especially meaningful.

These results suggest important lessons for city and regional policymakers. First, the locational considerations of actors trying to maximize accessibility will vary by county within the region. In some places, particularly in dense, urban San Francisco, generalized job accessibility is maximized by locating near especially dense employment agglomerations, irrespective of travel speeds. On the other hand, in the decidedly suburban job centers of Silicon Valley (in San Mateo and Santa Clara Valleys), congestion delays exhibit relatively substantial effects on employment accessibility.

Across the region as a whole, however,

Discussion: The Effects of Transit

The accessibility analyses presented in this and the following chapter focus solely on travel by automobile. While we also calculated speed and accessibility metrics for combined walking and transit travel between pairs of TAZs, the accessibility granted via these modes is substantially lower than derived from driving for the majority of the region. Although accessibility via walking/transit is comparably high for the most transit-friendly neighborhoods (taking just the top percentile of neighborhoods by transit/walk access, transit/walking access is 84% as great as is driving access), walking/transit access falls off very rapidly outside of this subset of neighborhoods (transit/walking access at the top decile of TAZs is 12% of that of driving, and transit/walking access in the median access TAZ is only 3% that of driving).

Additionally, when we calculated a hybrid measure of accessibility, so that the travel impedance to jobs in any given destination TAZ is the lower of driving or walking/transit, we found that this hybrid accessibility measure is nearly or exactly identical to our driving accessibility measure. As such, the inclusion of such multimodal accessibility would do little to change the results presented here. For individual origin-destination pairs, such as the trip across the Bay between downtown San Francisco and Oakland, transit can provide significantly enhanced access compared to peak hour auto travel. However, in our regional analysis these relative benefits are pooled with transit access from across the entire region, much of which is far poorer.

Our findings for the relative importance of destination proximity in conferring access appear especially robust when viewed in the context of our sole focus on automobility. If we were to grant independent value to accessibility conferred by other modes, the benefits of density would likely appear even greater.

and even in those counties where speed plays a relatively larger role in determining accessibility, it is clear that spatial proximity to destinations is by far the stronger predictor of access. While the fear of clogged roadways is perhaps the most common reason public officials cite for denying new development proposals in already built-up areas, discouraging such development, or pushing it to less congested, more outlying areas, is likely to have a negative effect on overall accessibility levels across a region's neighborhoods (Manville, 2013), even when we restrict our definition of accessibility to just that conferred by automobility. Conversely, the findings shown in Table 3.3 may justify a careful targeting of infrastructure enhancements aimed at speeding up vehicular travel. While positioning counties as low-proximity and high-speed is likely to be largely ineffectual in improving accessibility outcomes, our results indicate that improvements in travel speed can yield meaningful accessibility benefits, with some counties likely to see greater benefit than others. Provided that these increases in travel speed are achieved without freezing or reducing the number of nearby destinations, local traffic mitigation improvements may indeed yield better overall access outcomes for residents of affected neighborhoods. While we examine vehicular speeds in this analysis, local enhancements to travel speeds that do not involve capping or reducing destination density may involve other modes, whether walking, biking, or well-planned transit.

3.6 Comparison to Los Angeles

In previous work, the authors of this report carried out a similar analysis of the speed and proximity components of accessibility in the five-county Los Angeles metropolitan region (Mondschein et al., 2015). A comparison of the findings presented in this chapter with those from the Los Angeles analysis is illuminating for both the commonalities and differences that are exposed. Overall, our findings regarding the relative importance of speed and proximity in predicting access are corroborated; in both the San Francisco Bay Area and the greater Los Angeles region, we find that neighborhood-level proximity to job sites is a substantially stronger predictor of job accessibility than is travel speed.

The Bay Area and Los Angeles provide a useful juxtaposition for our analysis of job accessibility, as the two regions differ in multiple important respects. Namely, the Los Angeles region is substantially larger than the Bay Area (with 17.9 million people living across 3,999 traffic analysis zones, compared to 7.4 million people in 1,454 zones in the Bay Area). At the same time, Los Angeles is much more polycentric than is the Bay Area. Los Angeles exhibits many small employment centers, with a relatively minor share of total regional employment in any one center. Comparatively, the Bay Area exhibits two dominant employment centers in downtown San Francisco and the Silicon Valley, with these centers comprising a greater share of total employment than any comparable center in Los Angeles.

To facilitate comparison of our Bay Area and Los Angeles findings, we conducted a largely parallel set of data processing procedures, relying on travel demand model output from the respective metropolitan planning organizations to construct travel speed and travel time data at the level of the traffic analysis zone, and relying on National Establishment Time Series (NETS) data to construct job proximity measures. Additionally, we constructed our primary variables of interest in matching ways, using 10 km distance thresholds to calculate job proximity and average weekday peak-hour speed measures, and using weekday peak-hour travel times, along with an exponential function with a decay parameter of -0.2 to calculate job accessibility. Finally, we conducted a comparable set of statistical analyses in both regions, estimating both ordinary least squares (OLS) and hierarchical linear models to estimate the contributions of speed and proximity to accessibility.

Despite their differences in geography, the two regions show a strong similarity with respect to our primary finding: proximity to employment locations in both regions is a much greater predictor of employment accessibility than is travel speed. There are notable differences in our findings, however.

First, while the bivariate relationship between speed and accessibility is negative in both regions, this relationship is much stronger in Los Angeles, and, similarly, the positive contribution of speed to accessibility after controlling for job proximity is less strong in Los Angeles. This difference can be explained through the different relationships between speed and proximity in the two regions. As shown in Figure 3.3 (bottom right panel), the relationship between speed and proximity is relatively flat for most of the Bay Area, while a cluster of very dense, slow moving neighborhoods (corresponding to the city of San Francisco) generate an overall negative relationship between the two variables. By contrast, the negative relationship between speed and employment proximity is much more continuous throughout the Los Angeles region; even at relatively sparse density levels, increases in proximity to employment relates significantly to decreases in speed. It's this more consistent negative relationship between speed and proximity in Los Angeles that leads to speed's relative ineffectiveness in generating greater accessibility in the region.

In addition to exhibiting less of a negative relationship between speed and proximity – and thus between speed and accessibility – the amount of variance in accessibility that can be accounted for by our 10 km speed and proximity variables is lower in the Bay Area than in Los Angeles. This is likely a reflection of the greater peak densities in the Bay Area, which are reflected in a greater variance in accessibility for neighborhoods at the high end of the 10 km employment proximity distribution (as seen in the right panel of Figure 3.2). Given a set of locations with very high employment densities, a large set of neighborhoods within 10 km of these locations will show high values for our employment proximity measure. At the same time, the neighborhoods closest to these very high-density locations will show substantially higher accessibility values than will those neighborhoods with comparably high proximity values but that are farther away from the densest locations. This observation indicates that, for an ideal decomposition of accessibility into speed and proximity components, an exponential decay function for proximity (comparable to the travel time-based function used for accessibility) would be ideal. In the context of the present study, however, we calculate employment proximity based on distance thresholds, as this better corresponds to conceptions of proximity in the economic agglomeration literature.

Finally, in studying the relationships among speed, proximity, and accessibility in Los Angeles, we also employed hierarchical models to examine these relationships at sub-regional levels. However, our modeling procedure differed substantially in the prior Los Angeles work. Rather than testing for accessibility effects within- and between-geographies at the larger county level, we tested for these effects at substantially smaller community levels (we ended up with over 300 community units, within which we examined contextual effects of speed and proximity on accessibility). While the difference in grouping scale precludes direct comparison to the Los Angeles results, the qualitative differences we saw are worth noting. Namely, rather than seeing group-level speed and proximity effects outweigh the effects of within-group differences as we do in the Bay Area, we saw nearly the opposite in Los Angeles. After accounting for proximity, differences in speed within communities in Los Angeles did a substantially better job than differences in speed between communities in predicting a given neighborhood's accessibility levels. This finding indicates that small scale increases in travel speed can have a meaningful effect on job accessibility. The comparable model presented in this report for the Bay Area (the third column of Table 3.3) showed virtually zero average effect of within-county speed differences on accessibility. Again, however, the geographic scale of this model is substantially different from that of the Los Angeles model, and the finding presented would not contradict the Los Angeles finding of meaningful intra-community speed effects.

Chapter 4: Congestion and the Location of New Business Establishments

Chapter 2 outlined the different ways in which traffic congestion might affect the economic performance of regional economies. Theory predicts that traffic congestion should impose a cost on firms and industries; traffic congestion increases the cost of moving raw materials to factories, labor to worksites, inputs and outputs along supply chains, consumers to services, and products to consumers. However, there is limited empirical evidence in support of these intuitive and reasonable claims, and scholars have been unable to demonstrate in a robust way that traffic congestion diverts economic activity from congested to uncongested parts of regions, or to other regions entirely. As we showed in Chapter 3, access to workers tends to be highest in those parts of the San Francisco Bay Area where traffic congestion is the most severe. This finding gives rise to an interesting question: for a firm seeking to maximize access to potential employees and consumers for its goods and services, is it better to cluster tightly near other firms in the most congested parts of the region, or in less congested areas that remain part of the same regional economy? Each is a plausible firm response to congestion, and each is examined in the analysis described below.

In this chapter, we examine those factors that determine the location of new business establishments for some key, basic industries within the Bay Area. We pay particular attention to the extent to which traffic congestion influences the location decision of new firms in the Bay Area economy. As we described in Chapter 2, basic or tradeable industries are the lifeblood of regional economies. The economic performance of metropolitan areas is primarily determined by the goods and services that a region's basic industries produce and export to national and global markets. While many people in the Bay Area use Apple and Google's products, the primary consumption of these goods and services occurs outside of the Bay Area. Thus, the number of workers employed by Bay Area IT companies is not determined by how many of their products are consumed locally, but by how many of their products are consumed worldwide.

4.1 Key Industries

The data analysis for this report focuses on five primary industries (five basic, one non-basic): the advertising, entertainment, information technology, and securities and commodity industries, while a sixth "non-basic" industry, supermarkets and groceries, is analyzed for comparison. The industries were selected to cover a range of exporting sectors for which the nature of production is different, so that the findings presented here are not biased towards the particularities of a certain industry type. Each industry is defined using the North American Industrial Classification System (NAICS). The advertising industry is defined by code 5418. The IT industry is comprised of four sub-sectors: semiconductors (NAICS codes 333295 and 33451), electrical components (3344), computer and communications hardware (3341 and 3342), and software (518 and 5415). The entertainment industry is primarily comprised of two sub-sectors: the motion picture and video industry (5121) and the sound recording industry (5122). The securities and commodities industry is defined by code 523 and supermarkets and grocery stores are defined by NAICS code 4451. For each of these industries, except for groceries, the primary consumption of the goods and services they produce occurs outside of the Bay Area, making them basic, or tradeable sectors of the regional economy.

Table 4.1 below details total employment for each industry in the San Francisco region in 2009 and the number of new establishments in each industry for 2010 (this time period matches the most recent years for which travel delay data were available). Employment and new establishment counts were drawn from the National Establishment Time Series, while the average annual salary, which is also presented for each industry in 2009, is drawn from the Quarterly Census of Employment and Wages (QCEW).

Table 4.1 Descriptive Statistics for Key Industries in the Bay Area, 2009

	Advertising	Enter-tainment	Information Technology	Securities and Commodities	Grocery Stores
Total 2009 Employment	22,558	11,020	346,523	59,523	69,189
New 2010 Establishments	406	1247	1,337	5508	538
Average Annual Salary	$80,921	$80,963	$125,638	$239,865	$29,333

The San Francisco Bay Area is home to Silicon Valley, the world-renowned center of the Information Technology, or IT, industry, which is home to marquee technology companies such as Apple, Facebook, Google, Intel, and Twitter. The region hosts roughly 10 percent of the nation's IT jobs, despite accounting for only 3 percent of the nation's total employment. The IT industry is by far the largest export sector in the regional economy. Table 4.2 shows that, across the industries of enquiry, we see a wide range of average annual salaries. To place the wages paid by each sector in context, the region-wide average full-time salary was $66,290 across all sectors in 2009.

Figures 4.1, 4.2 and 4.3 below display the distribution of employment in each of the five industries across the region. The advertising industry is heavily concentrated within specific districts in the City and County of San Francisco. By contrast, the IT industry is mainly located in the region's "South Bay," which is home to Silicon Valley. As we would expect, the groceries industry is dispersed around the region, reflecting the region's residential patterns. The Bay Area entertainment industry is concentrated in the City and County of San Francisco, with other significant employment centers in Marin County and the East Bay. While not as geographically dispersed as grocery stores, the securities industry is found in a variety of mini clusters spread across the region.

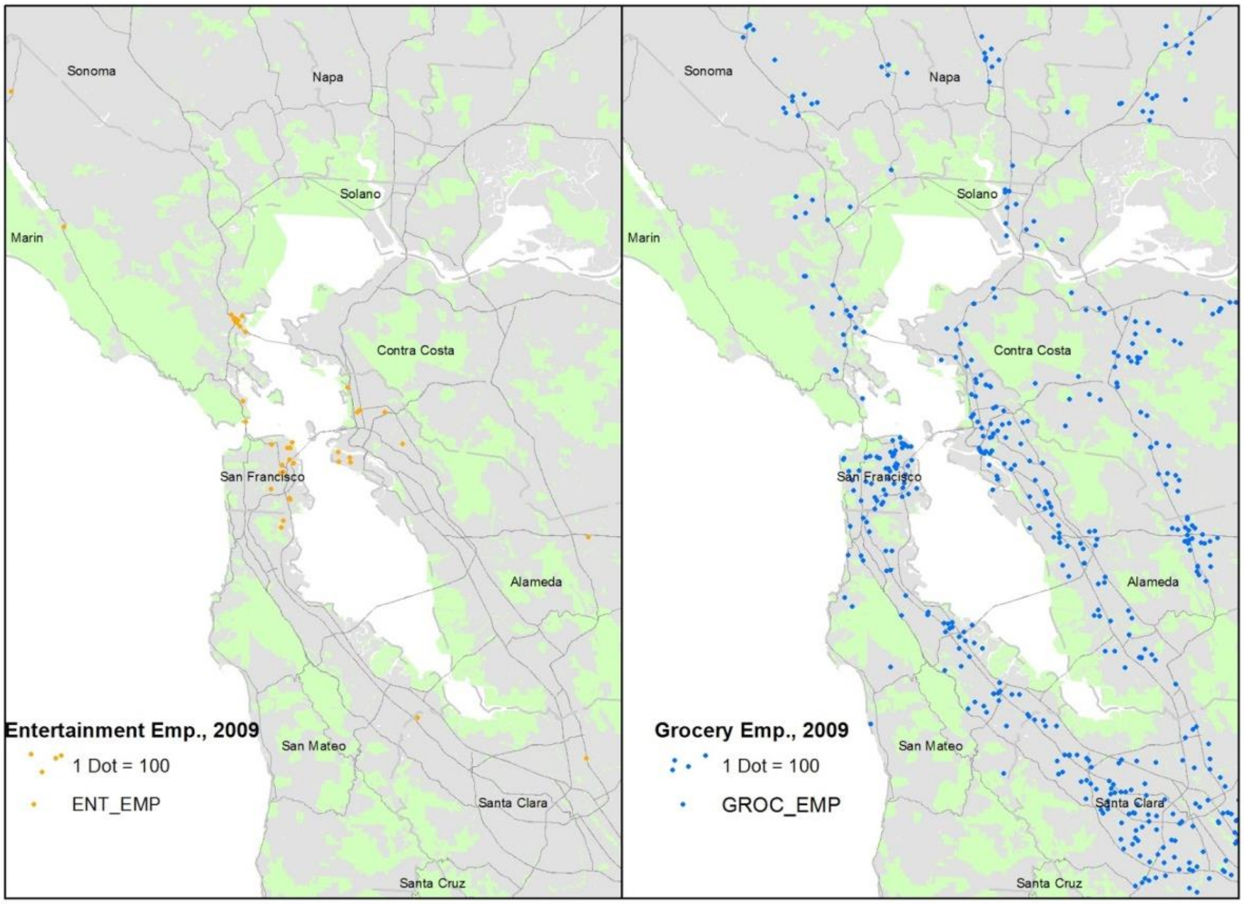


Figure 4.1 The Geographic Distribution of Grocery and Entertainment Industry Employment in Greater San Francisco in 2009

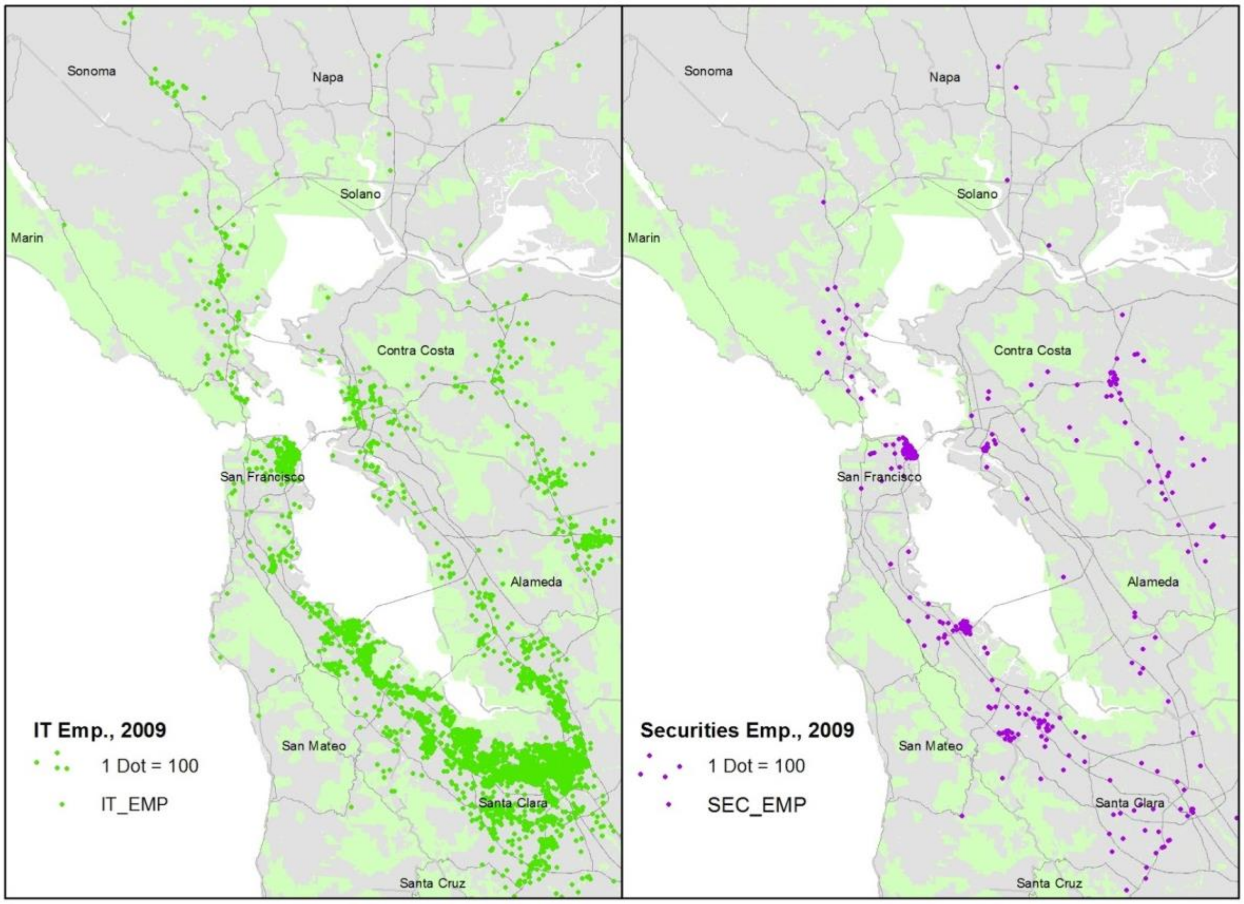


Figure 4.2 The Geographic Distribution of IT and Securities Industry Employment in Greater San Francisco in 2009

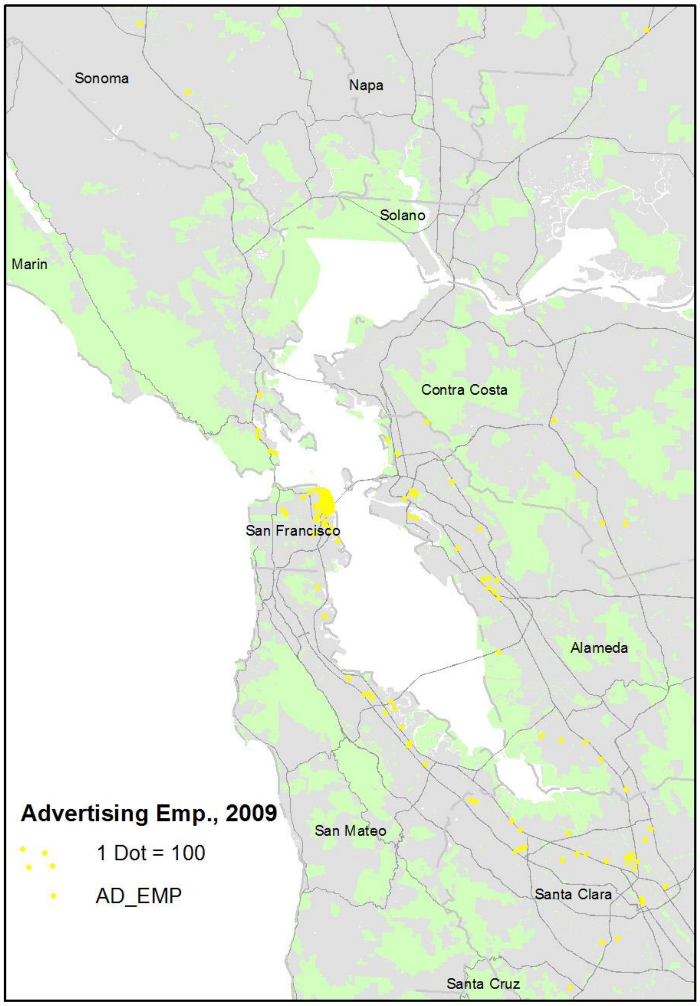


Figure 4.3 The Geographic Distribution of Advertising Industry Employment in Greater San Francisco in 2009

4.2 Statistical Analysis

The distribution of employment across our sectors of interest displays a high degree of localization (clustering), with the expected exception of (non-basic) grocery employment. Part of this spatial concentration, of course, has to do with physical geography. For example, there is no industrial activity in the region's state parks and national forests, or under its expansive bays. Another contributor to the observed spatial patterning of employment is land use zoning. A relatively small share of the total regional area is zoned for commercial or industrial activity. However, both of these constraints apply generally to grocery stores as well as office and industrial space, but we see far more clustering in the location of the "basic" industry employers than we do with grocery stores. As noted earlier, scholars believe that this clustering facilitates the firm-to-firm interactions that comprise production networks and enhance information spillovers.

There are many ways to explore the spatial relationship between firms of the same industry in a regional economy. But as we are particularly concerned with whether and to what extent traffic congestion affects regional economic development, we focus in this chapter on the location decisions of *new* business establishments for each industry. We do this because commercial location decisions are "sticky," in that it may take a lot of traffic congestion to push an already established firm out of a congested area into another part of the region, or to another region altogether. But for firms just setting up shop, the decision about where to locate must consider available space, the cost to rent or buy, access to customers, appropriately skilled labor, and other similar firms, and whether traffic, crime, or other disamenities make otherwise attractive locations less appealing. Therefore, our analysis centers on the location of new firms relative to two principal variables of interest: the location of other similar firms and traffic congestion.

There is a large body of research that analyzes the factors that influence the location of new business establishments (Rosenthal & Strange, 2003, 2010; Arzaghi & Henderson, 2008). For the most part, business location is framed as a discrete choice problem in which profit (utility) maximizing firms decide to locate in one site from among a set of alternative locations (Guimarães et al., 2004). The owners of new business establishments are assumed to be utility maximizers in that they seek to locate new establishments in those parts of a country or region where they believe their business has the best chance to succeed. The success of a given business establishment is determined by a multitude of factors, including (1) agglomeration economies, which were described in Chapter 2, (2) the cost of factors of production (such as wages and land), and (3) government actions such as tax rates, public safety, and land use regulations. However, this literature has been largely silent when it comes to examining the role that traffic congestion may play in determining the location of business activity within regions.

Today, modeling business location decisions, for the most part, relies on so-called "count" statistical models, such as Poisson or negative binomial (NB) regression models, both of which are derived from the Poisson distribution (Arzaghi & Henderson, 2008; Guimarães et al., 2004; Kim et al., 2008). The Poisson distribution is used to model counts of discrete events or occurrences (such as the number of businesses in a neighborhood or the number of police stops on a block, for example). Given that such occurrences are often rare, as well as the impossibility of a negative total, they do not conform to the normal distribution (or bell curve) common to so many studied phenomena. This skewed distribution of outcomes makes most linear statistical models used to study continuously distributed outcomes unsuitable for analysis of firm start-ups. Negative binomial models are often preferred in business location modeling because, unlike with Poisson models, they allow for a wider distribution in the outcome variable (referred to as over-dispersion). In cases where there is a large number of zeros amongst the observed unit of analysis (in this case, a large number of zones in which no new firms locate), a zero-inflated negative binomial model is preferred. The zero-inflated model adds an additional model component to account for an observed number of zeros that exceeds what would be expected from the best fitting negative binomial distribution. Such an excess of zeroes may arise due to the impossibility for enterprises to locate in particular places (because of zoning constraints, for example) or because new establishments determine that the characteristics of some sites would not enable them to maximize their profits (perhaps due to relative remoteness within a region).

The models presented below help us to explore the relationship between where new business establishments locate and existing patterns of same industry activity within the San Francisco region. Once a decision has been made to locate in the Bay Area, a business owner or manager can choose from roughly 1,400 neighborhoods or districts (defined here as traffic analysis zones, or TAZs), as permitted by local land use/zoning regulations. The median size of a Bay Area TAZ is 1.59 square kilometers. The outcome (or "dependent") variable in this analysis is the number of new business establishments in each industry sector that chose to locate in a given TAZ in 2010. In these models, the level of industry activity for each sector from each TAZ was calculated by taking the sum of industry employment at transportation network distance radii of 1, 1-5, 5-10, 10-20, 20-30 and 30-45 kilometers. For geographically large TAZs, small-threshold employment totals were calculated through a process of areal apportionment; for instance, if the average network distance within a TAZ was greater than 1 kilometer, we estimated the < 1 kilometer employment count by taking the observed 5 kilometer radius employment count and multiplying by the median ratio of areas defined by 1 km network radius thresholds and 5 km network radius thresholds. We then took the natural log of the employment level by each threshold so that the data would better approximate a normal distribution and reduce the influence of outlier TAZs. Statistical controls for population, racial/ethnic population distribution, average household income, and overall employment are included for each TAZ analyzed in this basic model.

The data for this statistical analysis are drawn from three primary sources: the National Establishment Time Series (NETS) proprietary micro dataset released by Walls and Associates, transportation network travel time data developed by the San Francisco Bay Area Metropolitan Transportation Commission (MTC), and socio-demographic data from the U.S. Census Bureau's American Community Survey (ACS). Please see Chapter 3 for descriptions of the NETS and MTC data in further detail. The ACS sociodemographic data provide population estimates averaged over the years 2005 through 2009 at the census tract level, from which we spatially interpolated figures at the closely matched traffic analysis zone level.

Two area household income control variables are included in our statistical models that allow for two different ways in which income might affect the location of new starts. Absolute income levels are continuous and used in the models in both linear and squared (or quadratic) terms. The squared term was included after inspection of the data revealed a relative abundance of firm starts near the middle of the neighborhood income spectrum and a relative paucity in both very high and very low income neighborhoods. Including this squared term allows for a non-linear effect of neighborhood/district income level on firm starts, such that the estimated effects of very low and high income neighborhoods on start-ups are muted and shift signs at the ends of the distribution. For example, while higher incomes are associated with more start-ups in middle-income areas, at the highest incomes further increases in income would be associated with *fewer* firm starts (such a scenario would correspond to a positive coefficient for the linear income term and a negative coefficient for the squared income term). In addition, each variable was standardized, which means the value of each variable for each TAZ has been divided by its standard deviation. This enables the relative effect of each coefficient for each variable to be directly compared with the other variables.

The employment and population in each TAZ were used to specify the zero component of the two-part modeling process. Each independent (explanatory) variable is "lagged" by one year compared with the dependent (outcome) variable in order to control for the fact that there is likely a lag between the conditions that lead to the decision to locate a new start-up firm and the start-up actually opening its doors for business. By having independent variables relate to 2009 while the dependent variable relates to 2010, we also account for the endogeneity of firm starts to total firm employment.

Figure 4.4, below (corresponding to the full model displayed in Table A.1 in the appendix), shows same-sector proximity predictors for new business establishments within the five industries of investigation in the San Francisco Bay Area in 2010. In these models, we restrict our analysis to the log of same industry employment, across our distance thresholds of interest, in addition to the control variables that we identify above.

These results confirm what theory would predict; namely, that firms of tradable industries seek to locate in close proximity to one another. That said, there are differences in the degree to which new establishments seek to locate close to existing levels of same-industry activity across the sectors under investigation. For each tradable industry, we see that the log of same-industry activity within a 5-kilometer range of a given TAZ best predicts the location of new starts for a given industry, at a level of significance of 95 percent or greater. Except for entertainment and IT industries, the level of same industry employment after a range of 10 kilometers (a distance of roughly 6.25 miles) does not significantly predict the location of new business establishments at a level of confidence of 90 percent or higher, all else being equal. For the IT industry, the log of same industry employment at a distance of up to 20 kilometers significantly predicts the location of new IT establishments, while for the entertainment industry, the log of same industry employment at a distance of 10-20 kilometers negatively predicts the location of new starts at a 90 percent level of confidence.

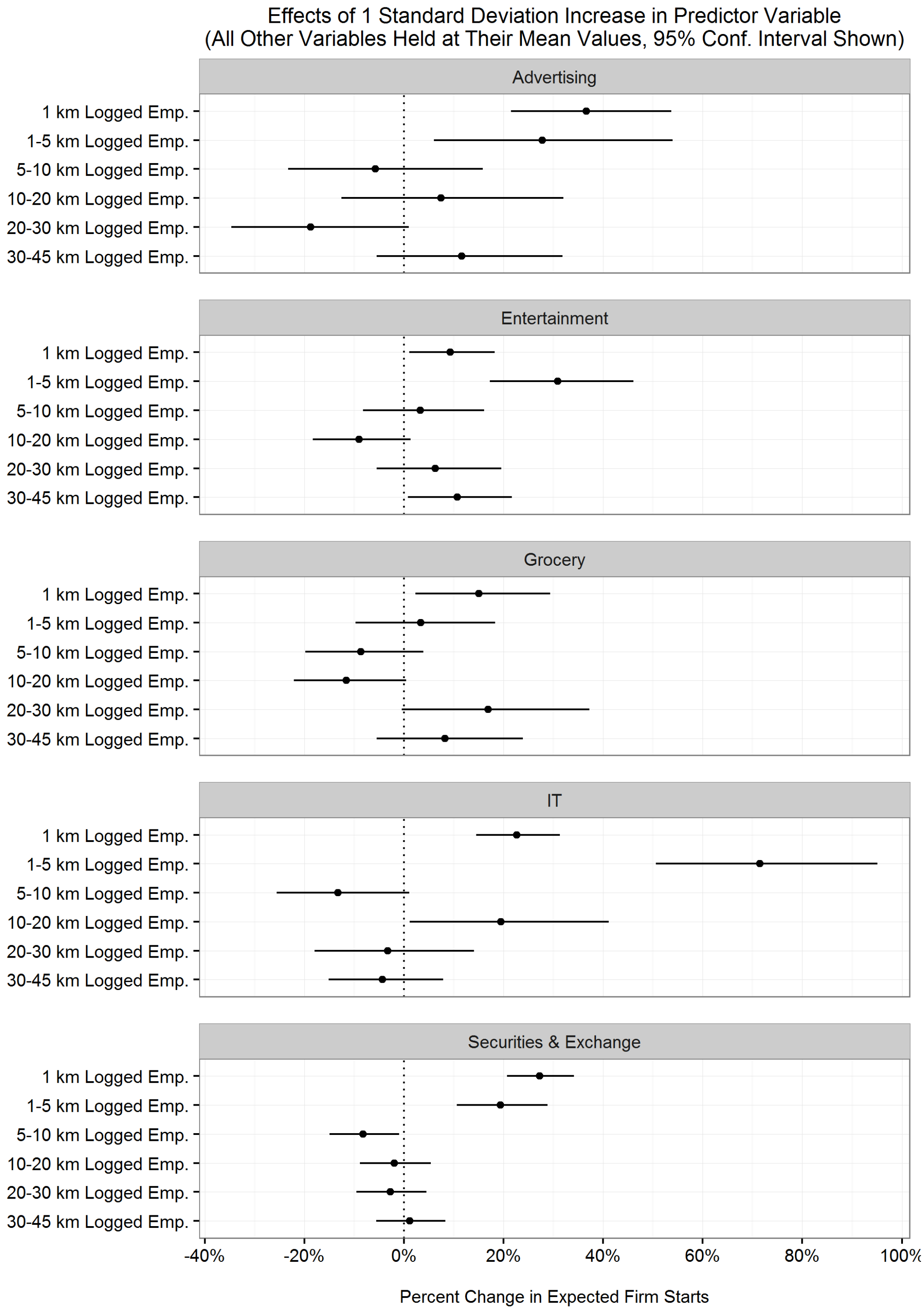


Figure 4.4 Effects of Employment Proximity Variables on Firm Starts, without Accounting for Speed

For the entertainment and IT industries, the log of same industry employment within the 1-5 kilometer threshold (roughly 0.6 - 3 miles) best predicts the location of new establishments for the respective industries, while for the advertising and securities industries, the log of same industry employment within 1 kilometer of a given TAZ best predicts the location of new starts. Overall, for these industries there is a clear localization effect. New establishments for each sector seek to locate close to existing patterns of same industry activity within the region. These findings add statistical evidence to figures 4.1-4.3 above, namely, that there is a high degree of spatial clustering for these industries within the regional economy.

Finally, the level of existing grocery store activity is a significant predictor of the location of new grocery establishments at a scale of 1 kilometer, with a 95 percent level of confidence, but unlike the other industries, not at greater scales. The association between new grocery stores and existing stores at this scale likely has to do with the nature of zoning, which limits where grocery stores can locate such that competitors are frequently located in close proximity. But grocery stores are otherwise distributed broadly to be convenient to consumers in all parts of the region. Thus, many cities are home to grocery stores, and many cities zone only a portion of their land for commercial activity, which means that grocery stores that serve such communities will, by virtue of the zoning process, be clustered together locally, but dispersed broadly. All in all, there is a high degree of clustering for the industries of investigation within the San Francisco region, which theory tells us is rooted in the desire of firms to reduce the costs of transacting with other firms and accessing information. The significance and effect of income, race/ethnicity, and population vary by industry and display no clear patterns.

4.3 The Effect of Congestion

To this point, the analysis presented has not accounted for the effect of traffic congestion on the location of new business establishments. To the models presented in Figure 4.4 above, a measure of congestion is also included in those depicted below. For each of five network distance thresholds (5, 10, 20, 30 and 45 km), the average speed from a given TAZ to all other TAZs within each of these thresholds was calculated for the AM and PM peak commute periods using the MTC data and process described in Chapter 3. The result is a measure of traffic delay from every neighborhood or district to every other neighborhood or districts at ranges from 1 kilometer (measuring local congestion effects) to 45 kilometers (measuring broader, sub-regional congestion effects). If congestion acts as a diseconomy of scale (is a cost of crowding), firms should locate in those parts of the region where congestion is relatively low (average speeds to and from other TAZs are high) and avoid those locations where congestion is relatively high (average speeds are low). For each industry, six separate models have been estimated to account for average speeds at each threshold described above. We display these effects for the 10 km speed range in Figure 4.5, below, with the full set of models for all speed ranges displayed in Tables A.2 – A.6 in the appendix.

For the advertising industry, with the exception of speed to TAZs at the 10 kilometer threshold, which is positive and significant at a 90 percent level of significance, travel speeds were not a significant predictor of the location of new establishments. This finding suggests that congestion has little impact on the location of start-ups in this sector. However, interesting results emerge from the analysis of the other industries. In the entertainment industry, the speed at which it is possible to travel to surrounding TAZs beyond a range of 10 kilometers or greater is a significant and negative predictor of new establishments, at a 99 percent level of confidence. In other words, slower moving parts of the region actually see more new establishments forming than faster moving parts of the region. This finding holds at the 10, 20, 30 and 45 kilometer thresholds for this industry. For the IT and securities and commodities industry, the picture is entirely different. For each distance threshold, faster speeds positively predict new establishments, at a level of confidence of 90 percent or greater. Finally, the speed variable has no impact on the location of new grocery starts, at any distance threshold, as expected.

Overall, the peak hour speed variable (which relates inversely to average levels of traffic delay) produces interesting results. In two of the five studied industries (Advertising and Groceries), traffic speeds have no effect on the location of start-ups; in two cases (IT and Securities) increased speeds have a positive effect on the location of new business establishments, and in one case (Entertainment) speed has a negative effect on the location of new activity. For each of the industries analyzed, the coefficients for proximity are in all cases more powerful predictors of firm start-ups than are the coefficients for the speed variables. Given the results of our analysis of the mobility-proximity-accessibility nexus reported on in Chapter 3, these results should not be surprising. Thus, the location of new tradable industry establishments is explained more by proximity to other similar firms than they are by the speed with which one firm can access other firms or workers can access job sites.

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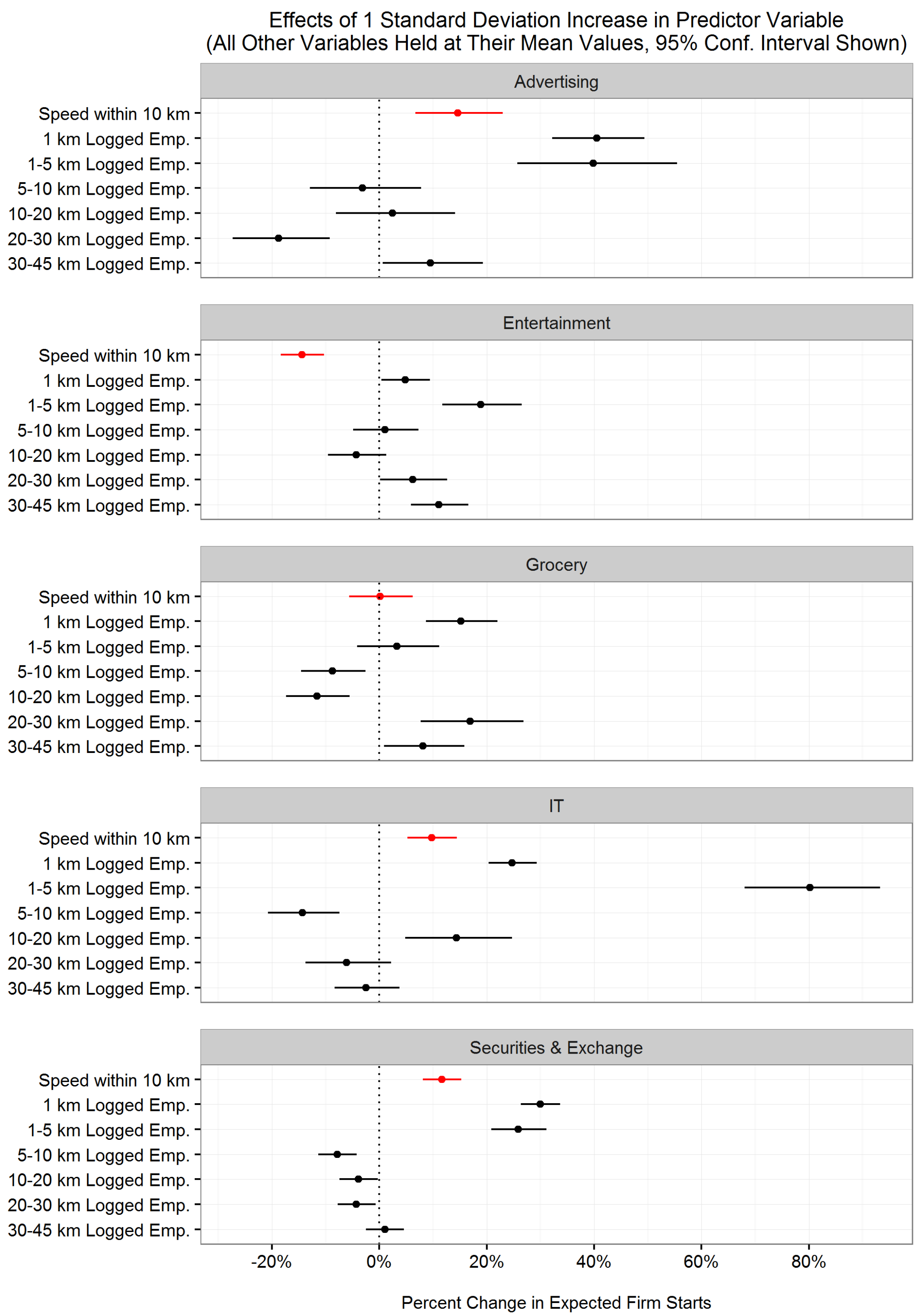

Figure 4.5 Effects of Employment Proximity Variables on Firm Starts, with Speed Predictor Included

The foregoing statistical models of firm start-ups displayed in Figures 4.4 and 4.5 align with the notion that accessibility to same-sector firms is a major factor in predicting tradable sector firm start-ups, and that it is physical proximity rather than free-flowing traffic that is the primary component of such accessibility. Recall from Chapter 3 that all-firm accessibility, as measured via negative exponentially weighted travel times to surrounding employment, is overwhelmingly driven by proximity, rather than by speed. Figure 4.6 below shows a similar relationship holding for the individual economic sectors under investigation here. As with the bottom-right panel of Figure 3.2 in Chapter 3, these graphs show a clear correspondence between greater proximity to firms of a given sector (as measured over a 10 km network radius) and greater accessibility (as represented graphically by warmer color tones), while there is little such correspondence between speed (again, as measured over a 10 km network radius) and accessibility.

This relationship between 10-kilometer speed, 10 kilometer sector-specific firm proximity, and accessibility is made numerically explicit in Table 4.2. As with the directly analogous Table 3.2 in Chapter 3, the sector-specific multilevel models relating speed and employment proximity to employment accessibility show that, for each sector, proximity matters to a much greater extent in predicting accessibility. As in Chapter 3, each initial speed, proximity, and accessibility variable is scaled by dividing by its standard deviation, allowing for direct comparison of coefficient values. The resulting ordinary least squares model shows that what held for all-sector employment access also holds for sector-specific access, with proximity to employment playing a proportionally much greater role than travel speed in predicting accessibility to any given sector's employment locations.

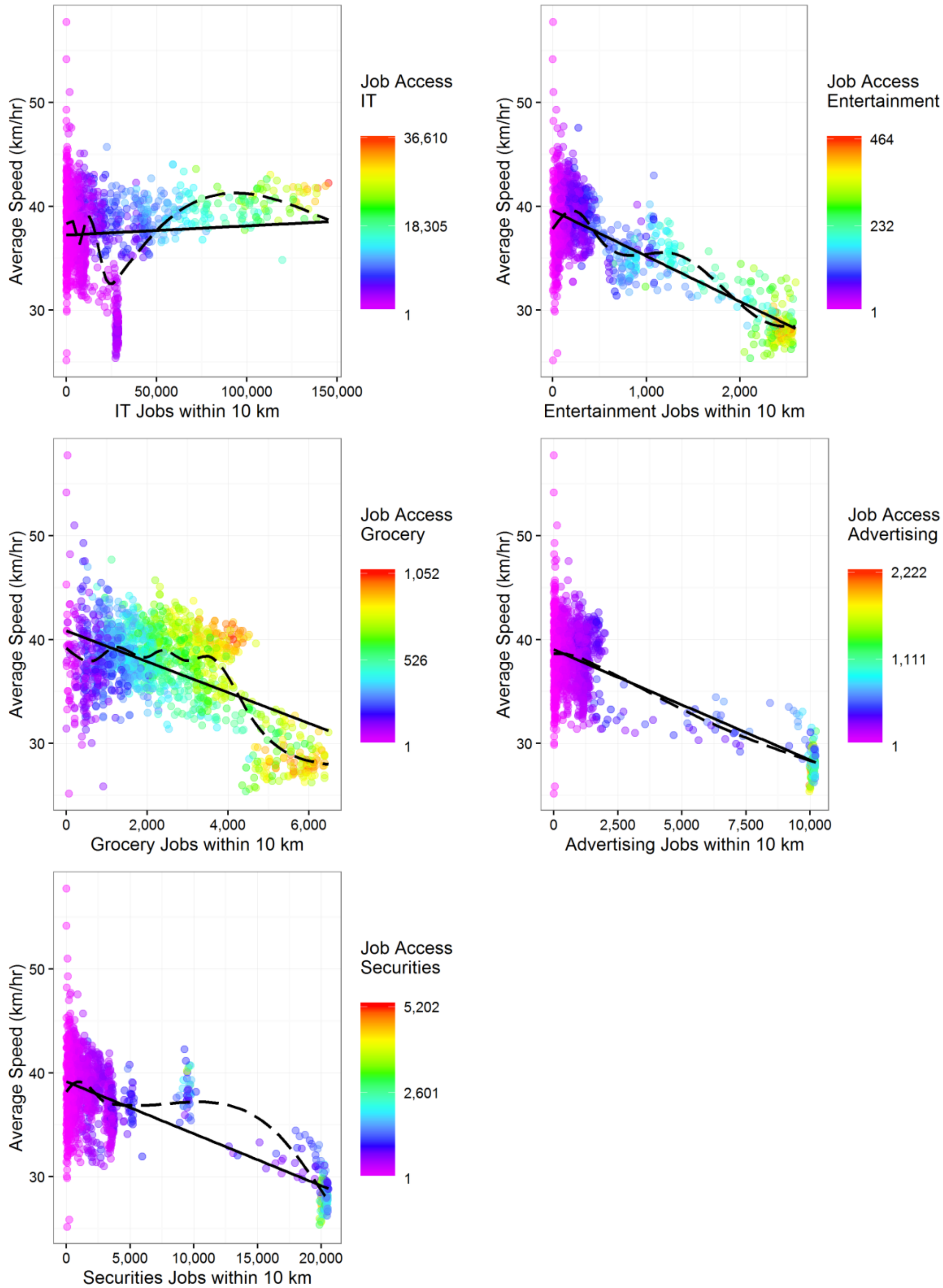

Figure 4.6 Relationships among Travel Speed, Employment Proximity, and Employment Accessibility for Specific Firm Sectors in Greater San Francisco in 2009

Table 4.2 OLS Model Output for Relationships among Speed, Proximity, and Accessibility Variables for Specific Sectors

	Dependent variable: Scaled Employment Access				
	IT Firms	Entertainment Firms	Grocery Firms	Advertising Firms	Securities Firms
	(1)	(2)	(3)	(4)	(6)
Peak-Hour Speed (km/hr; distance threshold = 10 km, scaled)	0.040**	0.041***	0.388***	0.145***	0.005
	(0.018)	(0.012)	(0.012)	(0.007)	(0.015)
Employment Proximity Count (distance threshold = 10 km, scaled)	0.916***	0.984***	1.075***	0.947***	0.930***
	(0.018)	(0.012)	(0.012)	(0.007)	(0.015)
Constant	0.0001	0.0001	0.0003	0.00004	0.00004
	(0.012)	(0.008)	(0.010)	(0.007)	(0.010)
Observations	1,453	1,453	1,453	1,453	1,453
R^2	0.789	0.909	0.844	0.934	0.858

(Standard errors in parentheses) $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

4.4 Comparison with Los Angeles

The findings presented in figure 4.4, where we measure the relationship between new firm starts and the log of same industry employment at different distance thresholds absent a measure of traffic congestion, support the results of similar work performed on the Los Angeles Metropolitan economy for the year 2008 (Mondschein et al 2015). For example, for Los Angeles, same industry employment was a positive, statistically significant predictor of new establishments (at a 95% level of confidence or greater) for the advertising and securities industries within a range of 10 kilometers, but not at a range greater than this distance. For the entertainment industry in Los Angeles, the level of same industry employment was a significant predictor of new establishments with a 99% level of confidence at scales of up to 45 kilometers, and for the IT industry, the level of same industry employment predicted the location of new establishments up to a scale of 20 kilometers. For the groceries industry, we see similar findings across the two regions. In Los Angeles, as is the case in the Bay Area, the log of same industry employment within a 1 km threshold is a significant predictor of new grocery establishments with a 95% level of confidence. The results from Los Angeles provide a high degree of support for the Bay Area findings and make it difficult to ascribe the Bay Area results to the particularities of the geography of the regional economy. In short, we are able to assert with a high degree of confidence that the location of new business establishments for our industries of interest is highly sensitive to the location of existing levels of same industry activity within the Bay Area economy.

Figure 4.5 (above) seeks to determine how traffic congestion, in addition to the log of same industry employment at different distance thresholds, affects the location of new business establishments for each industry. Again, it is useful to compare the findings from the Bay Area analysis to related work that has been performed for the Los Angeles regional economy (Mondschein et al. 2015). In Los Angeles, as is the case in the Bay Area, we find an inconsistent effect of congestion on the location of new business establishments. The findings in Los Angeles replicate the Bay Area results to the extent that physical proximity to existing levels of same industry activity, rather than free-flowing traffic, is consistently found to be the primary component of firm-to-firm accessibility. As is the case in the Bay Area, the level of congestion, from site-adjacent to the wider, sub-regional scale, has no statistical effect on the location of new grocery establishments in Los Angeles. For the advertising industry in Los Angeles, site-adjacent (within 1 km) traffic speeds are positively associated with new firm start-ups, though at a sub-regional (45 km) scale, traffic speeds are negatively associated with advertising firm start-ups. This finding is in marked contrast to the results from the Bay Area where travel speeds display no statistically significant effect on the location of new establishments in the advertising industry.

In the entertainment industry in Los Angeles, the impact of travel speeds on new establishments is opposite to the effect of travel speeds on the advertising industry in the region. For the entertainment industry, lower site-adjacent traffic speeds (i.e. higher levels of traffic congestion) increase the likelihood of entertainment firm start-ups, while sub-regional (10-45 km) traffic speeds are positively associated with start-ups. For the IT and securities and commodities industries in Los Angeles, area congestion is in most of the models unrelated to start-ups, though when there is a statistically significant effect it is always negative – at 1 km for the IT industry, and at the 1, 5, and 10 km radii for the securities and commodities industries. Recall that, in the Bay Area, increased speeds in the IT and securities and commodities industries have a positive effect on the location of new business establishments.

Overall, the combined findings from the Bay Area and Los Angeles display no consistent congestion effect on the location of new establishments either across or within industries. However, for each of the industries analyzed, the coefficients for proximity are in all cases more powerful predictors of firm start-ups than are the coefficients for the speed variables

4.5 Interpretation

The analysis reported here provides clear evidence that firms of tradable industries in the San Francisco Bay Area seek to locate in close proximity to one another, often at relatively fine-grained spatial scales. By contrast, we find interesting, if ambiguous, results relating to the effect of congestion on the location of new business establishments. For the advertising and groceries industries, traffic speeds have no effect on the location of start-ups. For the IT and securities industries, increased speeds have a positive effect on the location of new business establishments, and for entertainment, speed has a negative effect on the location of new activity.

These finding suggests that firm-to-firm interactions and information sharing occurs at highly localized scales. Given the role that proximity to other firms plays in shaping the location of new establishments across the industries studied here, it stands to reason that the transportation network should play a role in shaping the location of new establishments. After all, the efficiency with which it is possible to travel along different segments of the transportation network should directly influence accessibility to suppliers, similar firms, labor, and customers. The findings reported here thus might be interpreted in two ways, which are not mutually exclusive. At a local level, our results suggest that congestion plays a relatively inconclusive role in shaping the location of new establishments in the Bay Area industries examined here. However, at a regional level, it is reasonable to make the case that firms in tradable industries might be seeking to mitigate the effects of congestion on firm-to-firm interactions by locating in even closer proximity to one another than they might otherwise. In other words, to overcome travel delay and travel time unreliability at the regional scale, firms have located in close proximity to one another where they can reduce the effects of travel.

Chapter 5: Conclusion

This report has examined the effects of traffic delays on the accessibility and economic vibrancy of the San Francisco Bay Area, as a companion study to a similar analysis recently completed for Los Angeles (Mondschein, et al., 2015). In a nutshell, we find that proximity to jobs in the San Francisco Bay Area, regardless of congestion levels, contributes far more to employment access than do variations in traffic delays. This top line finding is identical to what we found in Los Angeles – a metropolitan area that is geographically, economically, and culturally distinct from the Bay Area.

The San Francisco Bay Area and greater Los Angeles are two of the largest, most expensive, and most congested metropolitan areas in the U.S. Why do residents go to all of the expense and trouble to live there, and why would firms choose to locate in such expensive, congested regions? Why is there not an exodus to cheaper, less congested cities in California or elsewhere like Bakersfield, Eureka, or Redding?

Access. Households and firms crowd into cities because jobs, friends, medical care, farmers' markets, and so much more are more easily accessed via the congested streets and roads of cities than via the free-flowing roads in small towns and rural areas. This conundrum – that access is often greatest where traffic is heaviest – is at the heart of the analyses in this report. No one likes being stuck in traffic, and all things equal, access is always greater with fewer traffic delays than with more. But the analyses presented here have shown quite clearly that, when it comes to access, all things are rarely equal, and that crowding things together in cities (i.e. increasing proximity) tends to give more to access, than the traffic delays common in densely developed areas take away.

We do find some interesting contrasts in our analyses of the effects of traffic delays on access in the Bay Area and Los Angeles – which should bring considerable relief to some denizens of the Bay Area who are adamant about the uniqueness of the place. First, we find far more concentration of employment in the Bay Area than LA – where the City of San Francisco and Silicon Valley account for a large share of total regional employment. Los Angeles, by contrast, is the consummate polycentric city, with many job centers spread around the region. Second, we find that variations in region-wide congestion levels (measured in terms of peak period speeds) in the Bay Area contribute more to variations in access than they do in Los Angeles. In particular, congestion notably reduces job access in Silicon Valley, in contrast to both the City of San Francisco and the Los Angeles region more generally – where proximity is king almost regardless of traffic levels. And finally, congestion and job access levels vary substantially from county to county in the Bay Area (say, between Alameda County and Santa Clara County), while traffic variations *within* these sub-regions appear to have little effect on job access. This too contrasts with Los Angeles, where we found that, within neighborhood-scaled sub-regions, variations of traffic delay (say, between more and less congested parts of Santa Monica) do meaningfully affect job access. The scales of the sub-regional analyses vary between the Bay Area and Southern California, inviting further investigation of these relationships. Still, the wholly different patterns of intra-county relationships between speed, proximity, and access in the City of San Francisco compared to either other Bay Area counties or Southern California subregions reinforce our conclusion that rules of thumb don't yet exist for understanding congestion's relationship to access, and policies and interventions to improve access are unlikely to be one-size-fits-all.

With respect to our analysis of the effects of peak-hour congestion levels on firm start-ups, we find strong and consistent effects of proximity to other similar firms on the likelihood of a firm start-up in a given area, across the tradeable industries examined in our analysis. These results strongly support the extensive literature on the effects of agglomeration on new firm locations, and they are consistent with what we found in our recent study of metropolitan Los Angeles (Mondschein, et al., 2015). And like our companion study of Los Angeles, we generally find inconsistent and uncertain effects of traffic delays on start-ups in the San Francisco Bay Area. While our models do turn up some statistically significant effects of congestion on start-ups in various industries across various geographic thresholds, for the most part congestion exerts little effect on start-ups (in dramatic contrast to proximity) and no obvious patterns emerge when apparent effects are present for particular industries over particular distances.

The novel research presented here for the San Francisco Bay Area, and in concert with our companion study of metropolitan Los Angeles, adds considerable support to the emerging consensus arguing for a shift from a mobility-focused view of how transportation networks perform, to an access-focused view of how urban systems (including their transportation systems) perform. Mobility – in cars, in trucks, via public transit, and by bike and foot – is a means to access, and not an end in itself. This shift in perspective is integral to the smart growth movement touted by many urban designers and planners, and exemplified by vibrant, older cities like San Francisco. This accessibility focus is also behind a burgeoning complete streets movement that seeks to evaluate streets as multi-purpose venues for economic and social activity, travel among them, rather than to hold the more traditional view that the success of streets is measured solely in terms of the volume and velocity of the motor vehicles they convey.

We conclude from the empirical analysis for the San Francisco Bay Area presented in this report, and in our recent, companion analysis for Los Angeles, that transportation network delay, infuriating though it may be, is at best an indirect measure of the ease and quality of social interactions and economic transactions that are the *raison d'être* of cities and their transportation systems. There are indeed effective ways to mitigate and manage urban traffic congestion (that we do not review in detail in this report), though we would note that such tools are spreading haltingly, in spite of their proven success, implying that they may be less politically palatable than congestion itself.

We could, for example, greatly expand street and freeway capacity, though this would be very expensive, would require the displacement of many homes and businesses, and in the minds of many would makes cities less sustainable and human-scaled. We could conversely ration scarce road capacity, through approaches as crude as cutting the eligible pool of motor vehicles in half with odd-even license plate days, to elegant solutions like variable electronic road pricing that would adjust the cost of driving to bring road supply and travel demand in balance to keep street and freeway traffic moving smoothly. Neither of these approaches has gained much political traction, despite considerable support for road pricing among many experts. This state of affairs has led noted political economist Anthony Downs to describe traffic congestion as not an intractable problem, but the most politically palatable solution to the problem of the demand for urban road space regularly exceeding the supply (Downs, 2004).

As we have shown in this analysis, access – which we define as the ability of travelers to avail themselves of economic and social opportunities in space – is a function of both speed and proximity. This speed/proximity tradeoff is at the heart of regional economic theory, as well as at hotly debated public meetings, where proposals for new, larger developments in already congested areas are fervently discussed, and often fervently opposed. To help inform such debates, we unambiguously found in this analysis of traffic and employment data for the San Francisco Bay Area, and in our companion analysis of metropolitan Los Angles, that proximity (in terms of adjacent development), rather than speed, is the much more critical element in determining the actual opportunities to reach desired destinations. In the Bay Area and LA, in other words, it's location, location, location, and not faster, faster, faster. Our findings lend no support to the idea that traffic congestion, even in a crowded, expensive region like the Bay Area, is chasing away new businesses (though we did not analyze this question directly in this analysis). What we did analyze directly and what we did not find was any evidence that chronic traffic congestion is driving businesses out to less congested parts of the Bay Area.

Our findings offer insights for planners and policy makers struggling to manage growth pressures in already built-up and congested areas, and suggest that transportation and land use decision makers might re-evaluate how they consider new development proposals in such areas. Likewise, we hope this report reinforces the need to consider the land use and accessibility context when considering transportation investments and policies and regional or local scales. Rather than focusing on predicted changes to link-level travel flows and intersection level-of-service measures, or on vague notions of the value of low or high densities in theory, planning officials would be wise to consider explicitly how predicted changes in neighborhood level speed and destination proximity will affect residents' access to destinations. As we have shown here, this access can be measured and evaluated in a consistent manner.

We acknowledge that universal measures of accessibility such as the job accessibility measures developed for this and our LA analysis may be insufficient for making this case to skeptical residents that increased development densities will increase their accessibility despite the accompanying increase in traffic congestion. When a resident shows up to a public hearing concerned about traffic, he is not there to debate how that development might change access to thousands of jobs for thousands of residents. Instead, he is concerned about *his* ability to reach urban amenities such as grocery stores, health care, or any of the other destinations that may or may not be served by the density around them. So while residents and workers in the aggregate may broadly benefit from increases in nearby employment density, individual residents may be made worse off by increasing density and the traffic delays it engenders, reducing access to households' everyday destinations in the process. As we noted in our analysis of Los Angeles, we might term this "the congestion conundrum," as it is at the heart of debates over the future of the Bay Area.

While novel in many respects, we need to note a few caveats here. First, while we did include peak hour travel speeds for public transit, biking, and walking in our preliminary analysis of Bay Area data, as discussed in Chapter 3 these had essentially no effect on our results so we ultimately focused solely on access as measured along vehicular networks at estimated vehicular speeds. Second, additional research on within-region trade-offs between proximity and speed can turn the conceptually novel findings presented in this Bay Area and our companion study for Los Angeles into decision-support tools for public officials. While our analyses present a compelling picture of the overall shape of these trade-offs at particular points in time for the Bay Area and Los Angeles, attributions of cause and effect would be greatly aided by the use of time series data. In order to make strong claims about the accessibility effects of changes over time to proximity and speed, it is important to directly assess such changes. Such time series analyses are not trivial to carry out; in addition to expanding the amount of data that need to be collected, they also require that estimations of zone-to-zone travel speeds be not just internally consistent within a given year, but consistent across years. Still, given the analytical benefits of consistent time series analyses of congestion and its effects, the collection of such data is needed if we are to begin employing conceptually and empirically sound access evaluation planning tools.

Finally, and as noted in our companion report for Los Angeles as well, analysts can better inform transportation and land use decisions by analyzing more specific community-level factors that influence the contextual effects of speed and proximity differences. Such statistical modeling can be done within a hierarchical framework similar to that employed in the models depicted in Chapter 3. In such a framework, various community-level attributes – such as job density in surrounding communities, the presence of highway infrastructure, etc. – can be used to predict where within-community differences in speed and proximity will be more influential with respect to accessibility levels. Along these lines, contextual influences on the speed-proximity-accessibility nexus can also be investigated through the use of structural equation models, similar to those reported by Levine et al. (2012) in their assessment of between-region predictors of accessibility. Such equations allow for the explicit modeling of the interactions among a host of inter-related factors, and can provide decision-makers with a better feel for potentially complex causal pathways. Overall, we expect that continued investigation and an increased understanding of the complex relationships among speed, proximity, and accessibility will further transportation planners' ability to provide useful information to communities and officials as they evaluate opportunities for growth and infrastructure investment in the years ahead.

The bottom line of our analysis is that traffic congestion and its effects on regional economies are far more subtle and complex than travelers, and the people whom they elect, generally believe. Are traffic delays maddening? Without a doubt. Are the highest job access areas in the San Francisco Bay Area and metropolitan Los Angles also typically the most congested? Yes. So should proposals for new developments in already built-up and congested areas be rejected out of hand on the grounds that they will worsen traffic delays? Not so fast.

Appendix

Table A.1 Predictors of New Establishments by Sector, 2010

	Firm Starts Dependent Variable, by Sector:				
	Ad.	Ent.	IT	Sec. & Comm.	Grocery
	(1)	(2)	(3)	(4)	(5)
Log Same Industry Employment within 1 km	0.312***	0.089**	0.204***	0.241***	0.140**
	(0.060)	(0.040)	(0.035)	(0.027)	(0.060)
Log Same Industry Employment w/in 1-5 km	0.245**	0.269***	0.539***	0.177***	0.033
	(0.095)	(0.056)	(0.066)	(0.385)	(0.069)
Log Same Industry Employment w/in 5-10 km	-0.059	0.032	-0.142*	-0.086**	-0.091
	(0.105)	(0.060)	(0.078)	(0.039)	(0.066)
Log Same Industry Employment w/in 10-20 km	0.072	-0.095*	0.178**	-0.020	-0.123
	(0.105)	(0.055)	(0.085)	(0.037)	(0.065)
Log Same Industry Employment w/in 20-30 km	-0.208*	0.061	-0.033	-0.028	0.156*
	(0.111)	(0.060)	(0.084)	(0.037)	(0.082)
Log Same Industry Employment w/in 30-45 km	0.110	0.102**	-0.044	0.011	0.079*
	(0.085)	(0.048)	(0.061)	(0.035)	(0.069)
Total Population in TAZ	0.157***	0.206***	0.127***	0.263***	0.135***
	(0.039)	(0.028)	(0.033)	(0.026)	(0.042)
Median Income in TAZ	0.110	0.172	0.325**	-0.195*	-0.420**
	(0.225)	(0.144)	(0.144)	(0.108)	(0.207)
Median Income Squared in TAZ	-0.036	-0.165	-0.174	0.370***	0.212
	(0.230)	(0.137)	(0.133)	(0.097)	(0.214)

Percent Hispanic and Black in TAZ	-0.194**	-0.118**	-0.216***	-0.327***	-0.041
	(0.089)	(0.046)	(0.055)	(0.037)	(0.063)
Constant	-0.928***	-0.205***	-0.986***	1.130***	-0.760***
	(0.107)	(0.050)	(0.074)	(0.027)	(0.086)
Observations	1,454	1,454	1,454	1,454	1,454
AIC	1,680	3371	6485	3,992	2006
BIC	1,759	-3450	6564	4071	2085

(Standard errors in parentheses) *p<0.1; **p<0.05; ***p<0.01

Table A.2 Predictors of New Grocery Establishments by Sector, 2010

	Distance Threshold for Speed Independent Variable:					
	1 km	5 km	10 km	20 km	30 km	45 km
	(1)	(2)	(3)	(4)	(5)	(6)
Log of Same Industry Employment within 1 km	0.325***	0.146**	0.141**	0.146**	0.142**	0.137**
	(0.078)	(0.053)	(0.058)	(0.056)	(0.056)	(0.056)
Same Industry Employment w/in 1-5 km	-0.148	0.037	0.032	0.046	0.036	0.031
	(0.157)	(0.071)	(0.074)	(0.072)	(0.069)	(0.069)
Same Industry Employment w/in 5-10 km	0.061	-0.081	-0.092	-0.079	-0.085	-0.091
	(0.147)	(0.068)	(0.066)	(0.069)	(0.067)	(0.067)
Same Industry Employment w/in 10-20 km	-0.230*	-0.127	-0.124*	-0.142**	-0.120*	-0.118*
	(0.122)	(0.069)	(0.067)	(0.070)	(0.066)	(0.065)
Same Industry Employment w/in 20-30 km	0.043	0.160	0.156	0.159*	0.158*	0.195**
	(0.109)	(0.081)	(0.082)	(0.083)	(0.083)	(0.088)
Same Industry Employment w/in 30-45 km	0.194*	0.077	0.078	0.080	0.080	0.078
	(0.112)	(0.068)	(0.069)	(0.069)	(0.069)	(0.070)
Speed Variables	-0.072	0.023	0.001	0.046	0.044	0.084
	(0.091)	(0.056)	(0.059)	(0.058)	(0.055)	(0.057)
Total Population in TAZ	0.147	0.137**	0.135***	0.139***	0.141***	0.149***
	(0.093)	(0.045)	(0.042)	(0.042)	(0.043)	(0.043)
Median Income in TAZ	-0.607**	-0.453	-0.421**	-0.457**	-0.454**	-0.473**
	(0.248)	(0.211)	(0.212)	(0.212)	(0.211)	(0.209)
Median Income Squared	0.501*	0.215	0.213	0.240	0.235	0.240
	(0.265)	(0.213)	(0.218)	(0.216)	(0.215)	(0.213)
Percent Hispanic and	-0.008	-0.054	-0.042	-0.058	-0.053	-0.057

Black in TAZ	(0.075)	(0.065)	(0.066)	(0.066)	(0.064)	(0.064)
Constant	-1.077***	-0.761***	-0.760***	-0.766***	-0.769***	-0.775***
	(0.138)	(0.085)	(0.086)	(0.086)	(0.087)	(0.086)
Observations	927	1444	1453	1454	1454	1454
AIC	1258.488	2007.929	2007.934	2007.459	2007.447	2005.926
BIC	1335.799	2091.99	2092.437	2091.972	2091.96	2090.44

(Standard errors in parentheses) *p<0.1; **p<0.05; ***p<0.01

Table A.3 Predictors of New Advertising Establishments by Sector, 2010

	Distance Threshold for Speed Independent Variable:					
	1 km	5 km	10 km	20 km	30 km	45 km
	(1)	(2)	(3)	(4)	(5)	(6)
Log of Same Industry Employment within 1 km	0.556***	0.323***	0.340***	0.314***	0.313***	0.313***
	(0.083)	(0.065)	(0.061)	(0.060)	(0.060)	(0.060)
Log of Same Industry Employment w/in 1-5 km	0.078	0.256**	0.335***	0.273***	0.253**	0.242**
	(0.133)	(0.110)	(0.106)	(0.097)	(0.096)	(0.095)
Log of Same Industry Employment w/in 5-10 km	0.026	-0.064	-0.032	-0.029	-0.058	-0.056
	(0.142)	(0.105)	(0.107)	(0.108)	(0.105)	(0.105)
Log of Same Industry Employment w/in 10-20 km	-0.002	0.060	0.024	0.070	0.085	0.064
	(0.134)	(0.106)	(0.108)	(0.107)	(0.108)	(0.106)
Log of Same Industry Employment w/in 20-30 km	-0.118	-0.209*	-0.208*	-0.211*	-0.198*	-0.219*
	(0.155)	(0.112)	(0.111)	(0.111)	(0.113)	(0.114)
Log of Same Industry Employment w/in 30-45 km	-0.188	0.106	0.091	0.099	0.095	0.118
	(0.137)	(0.085)	(0.085)	(0.085)	(0.090)	(0.087)
Speed Variables	0.024	0.023	0.136*	0.092	0.042	-0.031
	(0.110)	(0.078)	(0.071)	(0.069)	(0.076)	(0.074)
Total Population in TAZ	-0.116	0.156***	0.169***	0.166***	0.164***	0.151***
	(0.104)	(0.040)	(0.039)	(0.039)	(0.041)	(0.042)
Median Income in TAZ	0.229	0.100	0.021	0.047	0.090	0.121
	(0.274)	(0.229)	(0.232)	(0.231)	(0.228)	(0.226)
Median Income Squared	-0.154	0.043	0.116	0.081	0.047	0.032
	(0.305)	(0.234)	(0.238)	(0.235)	(0.232)	(0.231)
Percent Hispanic and Black in TAZ	-0.177	-0.202**	-0.222**	-0.220**	-0.204**	-0.188**
	(0.105)	(0.090)	(0.091)	(0.091)	(0.091)	(0.090)

Constant	-1.576	-0.926***	-0.958	-0.944***	-0.935***	-0.925***
	(0.159)	(0.108)	(0.109)	(0.109)	(0.108)	(0.107)
Observations	927	1444	1453	1454	1454	1454
AIC	1034	1680	1678	1680	1682	1682
BIC	1111	1764	1763	1765	1766	1766

(Standard errors in parentheses) *p<0.1; **p<0.05; ***p<0.01

Table A.4 Predictors of New Entertainment Establishments by Sector, 2010

	Distance Threshold for Speed Independent Variable:					
	1 km	5 km	10 km	20 km	30 km	45 km
	(1)	(2)	(3)	(4)	(5)	(6)
Log of Same Industry Employment within 1 km	0.233***	0.078*	0.047	0.067*	0.096**	0.100**
	(0.049)	(0.043)	(0.043)***	(0.040)	(0.040)	(0.040)
Log of Same Industry Employment w/in 1-5 km	0.163*	0.234***	0.173	0.203***	0.255***	0.273***
	(0.090)	(0.063)	(0.062)	(0.057)	(0.055)	(0.055)
Log of Same Industry Employment w/in 5-10 km	0.302***	0.028	0.010	-0.062	-0.007	0.035
	(0.086)	(0.060)	(0.060)	(0.061)	(0.060)	(0.060)
Log of Same Industry Employment w/in 10-20 km	-0.126	-0.095*	-0.044	-0.042	-0.139**	-0.120**
	(0.079)	(0.056)	(0.057)	(0.055)	(0.055)	(0.055)
Log of Same Industry Employment w/in 20-30 km	0.204**	0.072	0.060	0.053	0.015	-0.024
	(0.083)	(0.060)	(0.059)	(0.059)	(0.058)	(0.064)
Log of Same Industry Employment w/in 30-45 km	0.119*	0.097**	0.105**	0.100**	0.134***	0.121**
	(0.070)	(0.048)	(0.048)	(0.047)	(0.048)	(0.048)
Speed Variables	0.045	-0.046	-0.156***	-0.210***	-0.193***	-0.143***
	(0.068)	(0.050)	(0.047)	(0.041)	(0.038)	(0.041)
Total Population in TAZ	0.209**	0.202***	0.194***	0.188***	0.186***	0.187***
	(0.061)	(0.028)	(0.028)	(0.027))	(0.027)	(0.028)
Median Income in TAZ	0.273	0.182	0.211	0.246*	0.284**	0.253*
	(0.176)	(0.145)	(0.144)	(0.143)	(0.145)	(0.145)
Median Income Squared	-0.315*	-0.179	-0.204	-0.215	-0.241*	-0.215
	(0.188)	(0.138)	(0.138)	(0.137)	(0.138)	(0.138)
Percent Hispanic and	-0.030	-0.117**	-0.090*	-0.064	-0.079*	-0.095**

Black in TAZ	(0.052)	(0.047)	(0.047)	(0.047)	(0.046)	(0.046)
Constant	-0.664***	-0.203***	-0.215***	-0.227***	-0.232***	-0.217***
	(0.074)	(0.050)	(0.049)	(0.049)	(0.049)	(0.049)
Observations	927	1444	1453	1454	1454	1454
AIC	2041.977	3363.796	3361.765	3347.145	3348.122	3360.946
BIC	2119.289	3448.199	3446.267	3431.658	3432.635	3445.459

(Standard errors in parentheses) *p<0.1; **p<0.05; ***p<0.01

Table A.5 Predictors of New IT Establishments by Sector, 2010

	Distance Threshold for Speed Independent Variable:					
	1 km	5 km	10 km	20 km	30 km	45 km
	(1)	(2)	(3)	(4)	(5)	(6)
Log of Same Industry Employment within 1 km	1.078***	0.219***	0.221***	0.216***	0.211***	0.206***
	(0.061)	(0.038)	(0.036)	(0.036)	(0.036)	(0.035)
Log of Same Industry Employment w/in 1-5 km	-0.140	0.616***	0.589***	0.560***	0.538***	0.525***
	(0.085)	(0.073)	(0.070)	(0.066)	(0.066)	(0.066)
Log of Same Industry Employment w/in 5-10 km	0.221**	-0.155**	-0.155**	-0.110	-0.147*	-0.159**
	(0.092)	(0.078)	(0.078)	(0.078)	(0.077)	(0.078)
Log of Same Industry Employment w/in 10-20 km	0.027	0.149*	0.134	0.121	0.199**	0.193**
	(0.100)	(0.087)	(0.087)	(0.086)	(0.085)	(0.085)
Log of Same Industry Employment w/in 20-30 km	-0.020	-0.062	-0.063	-0.088	-0.077**	-0.009
	(0.106)	(0.086)	(0.085)	(0.085)	(0.085)	(0.084)
Log of Same Industry Employment w/in 30-45 km	-0.114	-0.035	-0.025	-0.003	-0.029	-0.056
	(0.084)	(0.063)	(0.062)	(0.062)	(0.061)	(0.061)
Speed Variables	-0.086*	0.073*	0.093**	0.159***	0.177***	0.190***
	(0.047)	(0.044)	(0.042)	(0.041)	(0.040)	(0.041)
Total Population in TAZ	-0.008	0.134***	0.132*	0.133***	0.137***	0.137***
	(0.051)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Median Income in TAZ	0.172	0.255*	0.250	0.201	0.205	0.210
	(0.149)	(0.149)	(0.148)	(0.147)	(0.146)	(0.146)
Median Income Squared	0.017	-0.107	-0.108	-0.081	-0.096	-0.109
	(0.142)	(0.138)	(0.136)	(0.135)	(0.134)	(0.134)
Percent Hispanic and	-0.083	-0.223***	-0.239***	-0.271***	-0.269***	-0.280***

Black in TAZ	(0.059)	(0.055)	(0.056)	(0.056)	(0.056)	(0.056)
Constant	-0.775***	0.101**	0.112**	0.100**	0.091**	0.087*
	(0.081)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Observations	927	1,444	1,453	1,454	1,454	1,454
AIC	2255	3968.771	3988.756	3978.691	3973.955	3972.069
BIC	2,333	4,053	4,073	4,063	4,058	4,057

(Standard errors in parentheses) *p<0.1; **p<0.05; ***p<0.01

Table A.6 Predictors of New Securities Establishments by Sector, 2010

	Distance Threshold for Speed Independent Variable:					
	1 km	5 km	10 km	20 km	30 km	45 km
	(1)	(2)	(3)	(4)	(5)	(6)
Log of Same Industry Employment within 1 km	0.725***	0.249***	0.262***	0.250***	0.244***	0.237***
	(0.040)	(0.029)	(0.028)	(0.027)	(0.027)	(0.027)
Log of Same Industry Employment w/in 1-5 km	0.009	0.176***	0.230***	0.211***	0.180***	0.176***
	(0.047)	(0.043)	(0.041)	(0.038)	(0.038)	(0.038)
Log of Same Industry Employment w/in 5-10 km	0.073	-0.088**	-0.082**	-0.048	-0.079**	-0.091**
	(0.047)	(0.040)	(0.039)	(0.039)	(0.039)	(0.039)
Log of Same Industry Employment w/in 10-20 km	0.011	-0.027	-0.040	-0.021	0.015	-0.010
	(0.041)	(0.037)	(0.037)	(0.036)	(0.037)	(0.037)
Log of Same Industry Employment w/in 20-30 km	-0.022	-0.031	-0.044	-0.038	-0.001	0.000
	(0.049)	(0.038)	(0.037)	(0.037)	(0.037)	(0.039)
Log of Same Industry Employment w/in 30-45 km	-0.104**	0.012***	0.010	0.000	-0.020	0.004
	(0.052)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Speed Variables	0.112***	0.015*	0.110***	0.159***	0.132***	0.072**
	(0.044)	(0.035)	(0.032)	(0.029)	(0.029)	(0.029)
Total Population in TAZ	0.174***	0.262***	0.273***	0.279***	0.278***	0.271***
	(0.039)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Median Income in TAZ	0.033	-0.204***	-0.251**	-0.281***	-0.272**	-0.246**
	(0.121)	(0.109)	(0.108)	(0.108)	(0.108)	(0.110)
Median Income Squared	0.104	0.375	0.413***	0.422***	0.413***	0.399***
	(0.114)	(0.098)	(0.098)	(0.097)	(0.097)	(0.098)
Percent Hispanic and	-0.097**	-0.333	-0.347***	-0.366***	-0.355***	-0.345***

Black in TAZ	(0.043)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
Constant	0.576***	1.131	1.124***	1.116***	1.121***	1.127***
	(0.051)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Observations	927	1444	1453	1454	1454	1454
AIC	3711.167	6456.025	6473.572	6457.507	6466.373	6480.885
BIC	3788.478	6540.428	6558.075	6542.021	6550.886	6565.398

(Standard errors in parentheses) *p<0.1; **p<0.05; ***p<0.01

References

Arzaghi, M., & Henderson, J. V. (2008). Networking off Madison Avenue. *Review of Economic Studies*, *75*(4), 1011–1038. doi: 10.1111/j.1467-937X.2008.00499.x.

Bartik, T. J. (1991). The effects of property taxes and other local public policies on the intrametropolitan pattern of business location. In H. W. Herzok, Jr. & A. M. Schlottmann (Eds.), *Industry location and public policy* (pp. 57-80). Knoxville: University of Tennessee Press.

Bertini, R. L. (2006). *You are the traffic jam: An examination of congestion measures*. Presented at the 85th Annual Meeting of the Transportation Research Board, Washington DC.

Boarnet, M. G. (1997). Infrastructure services and the productivity of public capital: The case of streets and highways. *National Tax Journal*, *50*(1), 39–57.

Boarnet, M. G., Kim, E. J., & Parkany, E. (1998). Measuring traffic congestion. *Transportation Research Record: Journal of the Transportation Research Board, 1634*, 93–99. doi: 10.3141/1634-12.

Broverman, N. (2008, October 15). TV ads, rallies: Measure R is game on*. Curbed Los Angeles*. Retrieved from http://la.curbed.com/archives/2008/10/measure_r_efforts_ramping_up.php.

Bruegmann, R. (2006). Sprawl: A compact history: University of Chicago

Carrion, C., & Levinson, D. (2012). Value of travel time reliability: A review of current evidence. *Transportation Research Part A: Policy and Practice*, *46*(4), 720–741. doi:10.1016/j.tra.2012.01.003.

Cao, X., & Mokhtarian, P. L. (2005). How do individuals adapt their personal travel? Objective and subjective influences on the consideration of travel-related strategies for San Francisco Bay Area commuters. *Transport Policy*, *12*(4), 291–302.

Cervero, R. 1988. Congestion, growth, and public choices. *Berkeley Planning Journal, 3*(2), 55–75. Retrieved from https://escholarship.org/uc/item/4q7459c8#page-1.

Chatman, D. G., & Noland, R. B. (2014). Transit service, physical agglomeration and productivity in US metropolitan areas. *Urban Studies*, *51*(5), 917–937. doi: 10.1177/0042098013494426.

Cheshire, P. C., Nathan, M., & Overman, H. G. (2014). *Urban economics and urban policy: Challenging conventional policy wisdom*. Cheltenham, UK: Edward Elgar Publishing.

Choo, S., & Mokhtarian, P. L. (2007). How do people respond to congestion mitigation policies? A multivariate probit model of the individual consideration of three travel-related strategy bundles. *Transportation*, *35*(2), 145–163.

Chorus, C. G., Molin, E. J. E., & van Wee, B. (2006). Travel information as an instrument to change car-drivers' travel choices: A literature review. *European Journal of Transport and Infrastructure Research, 6*(4), 335-364.

DeRobertis MS, P. E., Joseph Kott, P. H. D., & Lee, R. W. (2014). Changing the Paradigm of Traffic Impact Studies: How Typical Traffic Studies Inhibit Sustainable Transportation. *Institute of Transportation Engineers. ITE Journal*, *84*(5), 30.

Desliver, D. (2014, February 21). *Chart of the Week: How metro areas drive the U.S. economy.* Retrieved from http://www.pewresearch.org/fact-tank/2014/02/21/chart-of-the-week-metro-areas-drive-the-u-s-economy/

Downs, A. (2004). *Still stuck in traffic: Coping with peak-hour traffic congestion*. Washington, DC: The Brookings Institution.

Drennan, M., & Brecher, C. (2012). Can public transportation increase economic efficiency? *Access*, *40*, 29-33. Retrieved from https://escholarship.org/uc/item/3mk1v8gz#page-1.

Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In J. V. Henderson & J.-F. Thisse (Eds.), *Handbook of regional and urban economics* (Vol. 4) (pp. 2063–2117). Amsterdam: Elsevier.

Euchner, C. C., & McGovern, S. J. (2003). *Urban policy reconsidered: Dialogues on the problems and prospects of American cities*. New York and London: Routledge.

Feldman, M. P. (1994). *The geography of innovation* (Vol. 2). Springer Science & Business Media.

Fernald, J. G. (1999). Roads to prosperity? Assessing the link between public capital and productivity.

American Economic Review, *89*(3), 619–638. doi: 10.1257/aer.89.3.619.

Fields, G., Hartgen, D., Moore, A., & Poole Jr, R. W. (2009). Relieving congestion by adding road capacity and tolling. *International Journal of Sustainable Transportation*, *3*(5-6), 360–372. doi: 10.1080/15568310802260013.

Gelman, A., & Hill, J. (2007). *Data analysis using regression and multilevel/hierarchical models*. New York: Cambridge University Press.

Geurs, K. T., & van Wee, B. (2004). Accessibility evaluation of land-use and transport strategies: Review and research directions. *Journal of Transport Geography*, *12*(2), 127–140. doi:10.1016/j.jtrangeo.2003.10.005.

Giuliano, G., Agarwal, A., & Redfearn, C. (2008). Metropolitan spatial trends in employment and housing. Washington, DC: *Transportation Research Board*. Retrieved from http://onlinepubs.trb.org/Onlinepubs/sr/sr298giuliano.pdf.

Glaeser, E. L., & Kahn, M. E. (2004). Sprawl and urban growth. .In J. V. Henderson & J.-F. Thisse (Eds.), *Handbook of regional and urban economics* (Vol. 4) (pp. 2481–2527). Amsterdam: Elsevier.

Glaeser, E. L., & Kohlhase, J. E. (2004). Cities, regions and the decline of transport costs. *Papers in Regional Science*, *83*, 197–228. doi: 10.1007/s10110-003-0183-x.

Glaeser, E. L., & Gottlieb, J. D. (2009). *The wealth of cities: Agglomeration economies and spatial equilibrium in the United States* (No. w14806). National Bureau of Economic Research.

Graham, D. J. (2007). Variable returns to agglomeration and the effect of road traffic congestion. *Journal of Urban Economics*, *62*(1), 103-120.

Grengs, J. (2010). Job accessibility and the modal mismatch in Detroit. *Journal of Transport Geography*, *18*(1), 42–54. doi:10.1016/j.jtrangeo.2009.01.012.

Grengs, J., Levine, J., Shen, Q., & Shen, Q. (2010). Intermetropolitan comparison of transportation accessibility: Sorting out mobility and proximity in San Francisco and Washington, DC. *Journal* *of Planning Education and Research, 29*(4), 427–443. doi:10.1177/0739456X10363278.

Guimaraes, P., Figueiredo, O., & Woodward, D. (2004). Industrial location modeling: Extending the random utility framework*. *Journal of Regional Science*, *44*(1), 1-20.

Handy, S. L., & Niemeier, D. A. (1997). Measuring accessibility: An exploration of issues and alternatives. *Environment and Planning A*, *29*(7), 1175–1194.

Hymel, K. (2009). Does traffic congestion reduce employment growth? *Journal of Urban Economics, 65*(2), 127–135. doi:10.1016/j.jue.2008.11.002.

Hymon, S. (2008, October 30). A closer look at half-cent sales tax hike, Measure R. *Los Angeles Times*. Retrieved from http://articles.latimes.com/2008/oct/30/local/me-roadsage30.

Isserman, A., & Rephann, T. (1995). The economic effects of the Appalachian Regional Commission: An empirical assessment of 26 years of regional development planning. *Journal of the American Planning Association, 61*(3), 345–364. doi: 10.1080/01944369508975647.

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1992). *Geographic localization of knowledge spillovers as evidenced by patent citations*. Cambridge, MA: National Bureau of Economic Research. doi: 10.3386/w3993.

Kahle, David, and Hadley Wickham. (2013). "ggmap: Spatial Visualization with ggplot2." The R Journal 5.1: 144-161.

Kawabata, M & Shen, Q. (2006). Job accessibility as an indicator of auto-oriented urban structure: A comparison of Boston and Los Angeles with Tokyo. *Environment and Planning B: Planning and Design, 33*(1), 115–130. doi: 10.1068/b31144.

Kim, H., Waddell, P., Shankar, V. N., & Ulfarsson, G. F. (2008). Modeling Micro-Spatial Employment Location Patterns: A Comparison of Count and Choice Approaches. *Geographical Analysis*, *40*(2), 123-151.

Krugman, P. (1991). *Geography and trade*. Cambridge, MA: MIT Press.

Krugman, P. (1998). What's new about the new economic geography? *Oxford Review of Economic Policy, 14*(2), 7–17. doi: 10.1093/oxrep/14.2.7.

Krugman, P. R. & Obstfeld, M. (2003). *International economics: Theory and policy* (6th ed.). Boston, MA: Addison Wesley.

Kwan, M.-P., & Weber, J. (2003). Individual accessibility revisited: Implications for geographical analysis in the twenty-first century. *Geographical Analysis, 35*(4), 341–353. doi: 10.1111/j.1538-4632.2003.tb01119.x.

Levine, J., Grengs, J., Shen, Q., & Shen, Q. (2012). Does accessibility require density or speed? A comparison of fast versus close in getting where you want to go in US metropolitan regions. *Journal of the American Planning Association, 78*(2), 157–172. doi: 10.1080/01944363.2012.677119.

Levinson, D. M. (2013). *Access across America*. Minneapolis: Center for Transportation Studies, University of Minnesota. Retrieved from http://www.cts.umn.edu/Publications/ResearchReports/pdfdownload.pl?id=2560.

Levinson, D. M., & Krizek, K. J. (2005). *Access to destinations*. Bingley, UK: Emerald Group Publishing.

Lomax, T., Turner, S., Shunk, G., Levinson, H. S., Pratt, R. H., Bay, P. N., & Douglas, G. B. (1997). *Quantifying congestion*: *Final report* (Vol. 1). Washington, DC: Transportation Research Board. Retrieved from http://onlinepubs.trb.org/onlinepubs/nchrp/nchrp_rpt_398.pdf.

Lomax, T., Turner, S., Shunk, G, Eisele, W. (2015). Urban Mobility Scorecard. Retrieved from http://mobility.tamu.edu/ums/

Marshall, A. (1961). *Principles of economics* (9th ed.). London: McMillan.

Manville, M., Beata, A., & Shoup, D. (2013). Turning housing into driving: Parking requirements and density in Los Angeles and New York. *Housing Policy Debate, 23*(2), 350–375.

Mondschein, A., Taylor, B. D., & Brumbaugh, S. (2011). *Congestion and accessibility: What's the* *relationship?* Berkeley: University of California Transportation Center. Retrieved from http://uctc.net/research/papers/UCTC-FR-2011-05.pdf.

Mondschein, A., Osman, T, Taylor, B. D., & Thomas, T. (2015). *Congested Development A Study of Traffic Delays, Access, and Economic Activity in Metropolitan Los Angeles. Report prepared for the John and Randolph Haynes Foundation*

Mondschein, A., & Taylor, B. D. (2016, March). Is Congestion Overrated? Examining the Highly Variable Effects of Congestion on Travel and Accessibility.

Moretti, E. (2012). *The new geography of jobs*. New York: Houghton Mifflin Harcourt Publishing.

Muller, P. (2004). Transportation and urban form: Stages in the spatial evolution of the American metropolis. In S. Hanson & G. Giuliano (Eds.), The geography of urban transportation (3rd ed.). New York: The Guilford Press.

North, D. C. (1955). Location theory and regional economic growth. *Journal of Political Economy, 63*(3), 243–258.

Owen, A., & Levinson, D. M. (2015). Modeling the commute mode share of transit using continuous accessibility to jobs. *Transportation Research Part A: Policy and Practice*, *74*, 110–122. doi:10.1016/j.tra.2015.02.002.

Pike, A., Rodríguez-Pose, A., & Tomaney, J. (2006). *Local and regional development*. New York: Routledge.

Raudenbush, S. W., & Bryk, A. S. (1992). *Hierarchical linear models: Applications and data analysis methods.* Thousand Oaks, CA: Sage Publications

Rosenthal, S. S., & Strange, W. C. (2003). Geography, industrial organization, and agglomeration. *Review of Economics and Statistics, 85*(2), 377–393. doi: 10.1162/003465303765299882.

Rosenthal, S. S., & Strange, W. C. (2004). Evidence on the nature and sources of agglomeration economies. In J. V. Henderson & J.-F. Thisse (Eds.), *Handbook of regional and urban economics* (Vol. 4) (pp. 2119–2171). Amsterdam: Elsevier.

Rosenthal, S. S., & Strange, W. C. (2010). Small establishments/big effects: Agglomeration, industrial organization and entrepreneurship. In E. L. Glaeser (Ed.), *Agglomeration economics* (pp. 277-302). Chicago: University of Chicago Press.

Salomon, I., & Mokhtarian, P. L. (1997). Coping with congestion: Understanding the gap between policy assumptions and behavior. *Transportation Research Part D: Transport and Environment*, *2*(2), 107–123.

Schrank, D., Lomax, T., & Turner, S. (2010). TTI's 2010 urban mobility report powered by INRIX traffic data. *Texas Transportation Institute, The Texas A&M University System*, *17*.

Schrank, D., Eisele, B., & Lomax, T. (2012). *TTI's 2012 urban mobility report*. College Station: Texas A&M Transportation Institute, The Texas A&M University System. Retrieved from http://s3.documentcloud.org/documents/566377/2012-urban-mobility-report.pdf.

Shen, Q. (2001). A spatial analysis of job openings and access in a US metropolitan area. *Journal of the American Planning Association, 67*(1), 53–68. doi: 10.1080/01944360108976355.

Singerman, P. (2008). Repurposed federal economic development programs: A practitioner's perspective. *Economic Development Quarterly, 22*(2), 99 –106. doi: 10.1177/0891242408316439.

Stopher, P. R. (2004). Reducing road congestion: A reality check. *Transport Policy, 11*(2), 117–131. doi: 10.1016/j.tranpol.2003.09.002.

Storper, M. T., Kemeny, N., Makarem, T., & Osman, T. (2015). *The rise and decline of great urban economies: Los Angeles and San Francisco since 1970*. Stanford: Stanford University Press.

Sweet, M. (2011). Does traffic congestion slow the economy? *Journal of Planning Literature, 26*(4), 391–404. doi: 10.1177/0885412211409754.

Sweet, M. (2014a). Do firms flee traffic congestion? *Journal of Transport Geography*, *35*, 40–49. doi:10.1016/j.jtrangeo.2014.01.005.

Sweet, M. (2014b). Traffic congestion's economic impacts: Evidence from US metropolitan regions.

Urban Studies, *51*(10), 2088–2110. doi: 10.1177/0042098013505883.

Taylor, B. D. (2002). Rethinking traffic congestion. *ACCESS Magazine*, *1*(21).

Taylor, B. D., & Norton, A. T. (2009). Paying for transportation: What's a fair price? *Journal of Planning Literature, 24*(1), 22–36. doi: 10.1177/0885412209347156.

United Nations Population Division. (2015). Retrieved from: http://esa.un.org/unpd/wup/.

Wachs, M., & Kumagai, T. G. (1973). Physical accessibility as a social indicator. *Socio-Economic Planning Sciences, 7*(5), 437–456.

Weisbrod, G., Vary, D., & Treyz, G. (2001). *Economic implications of congestion*. Washington, DC: Transportation Research Board. Retrieved from http://onlinepubs.trb.org/onlinepubs/nchrp/nchrp_rpt_463-a.pdf.

Ye, L., Hui, Y., & Yang, D. (2013). Road traffic congestion measurement considering impacts on travelers. *Journal of Modern Transportation, 21*(1), 28–39. doi: 10.1007/s40534-013-0005-z.