Title
Transportation Behavioral Data and Climate Change

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Publication Date
2019

Peer reviewed|Thesis/dissertation

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By

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A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Energy and Resources

in the

Graduate Division

of the

University of California, Berkeley

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Fall 2019

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Abstract

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In 2017, transportation became the largest single source of greenhouse gas emissions from the United States. Globally, the 2014 Intergovernmental Panel on Climate Change report found that, without far more aggressive policies, "transportation emissions could increase at a faster rate than emissions from other energy end use sectors" reaching 12 Gt $CO_{2\text{-eq}}$/year by 2050 (Sims et al., 2014). The overwhelming challenge of combatting these emissions is made far more difficult by the fact that so little is known about transportation behavior.

To use a cliché – if we can't measure it, we can't manage it. And transportation must be managed if we are to avoid the most catastrophic consequences of climate change. In this dissertation, I propose that better data collection is necessary to achieve reduction of transportation-related emissions. Happily, advances in technology make this more feasible today than at any time in the past. The costs of massive computing resources have gone down, the world is swarming with mobile devices like smartphones and connected cars collecting massive (if messy) amounts of data, and new techniques in data science and machine learning have emerged to help get clean answers out of all that data in a privacy-appropriate manner. In some cases, these new techniques will displace older ones. In other cases, the old ways have inherent advantages. In other cases yet, fusing new and old techniques will yield the most productive results.

In Chapter One, I lay out a framework to organize the types of transportation behavioral data that must be collected regularly to adequately measure and manage transportation's impact on climate. This builds on classic climate impact frameworks, adapting them to the particular measurement challenges presented by transportation. In Chapter Two, I provide a history of US transportation data collection since World War II as well as a review of traditional, modern, and emerging transportation data collection technologies. I then map each technology onto each behavioral data collection need identified in Chapter One, matching each behavior to the best respective data collection technique.

Chapters Three and Four provides an example of analysis done using the traditional data collection techniques, notably Household and Commercial Travel Surveys, to explore changes in PMT related to shopping and retail freight since 1969, as well as freight for fuel transportation. They demonstrate and take advantage of the key benefits of traditional techniques: that they go back in history, that they collect clearly stated trip purposes, vehicle occupancies, demographics (including gender, an important demographic but particularly difficult to deduce from the new data collection sources), trip distances, chaining behavior, commodities logged, and more. As it turns out, these benefits are

critical: the historical trends of the past 40 years allow behavioral insight that would not have been possible with a shorter term study, and gender dynamics are key to understanding the behaviors at hand.

However, the analysis in Chapters Three and Four also highlights some of the key limitations of survey-based analysis. The fact that data was only collected every five to ten years severely limits the analysis, such as limiting the exploration that can be done on the impacts of the Great Recession. In addition, fallibilities in human memory are especially pronounced in short trips, trip chains, and non-work related trips, all of particular importance to this study.

Chapters Five lays out theoretically, and then Chapter Six demonstrates via case study in India, how personal GPS diary devices can be used to log detailed data about individual trips. It demonstrates the key benefit of this data – highly individualized characteristics. Taking the example of vehicle electrification, this chapter demonstrates two ways such granular data is important: in one example, such data to give feedback to an individual to influence their car buying behavior. In the second, the granularity found with this new data collection techniques reveals the importance of highly localized policy making and emissions modeling based on driving patterns in different cities.

Chapter Seven uses the emerging technology of mass amounts of locational data, collected passively via smart phones, to explore how urban density at home and work interacts with total, work-related, and non-work-related miles driven. This demonstrates the great strength of this type of data – massive sample size combined with high spatial granularity and longitudinal data collection. These strengths enable the analysis at statistically meaningful scale of patterns across many geographies, individuals, and times of year. Thus, this data can shed light on questions about the relationship of density and miles travelled which previously have not been answered conclusively due to data constraints.

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Figures, Tables, and Equations

DEDICATION

To Dr. Lee Schipper, who knew how to find the fun in transportation data.

ACKNOWLEDGEMENTS

For their financial support, I thank the National Science Foundation Graduate Research Fellowship and the Berkeley Fellowship.

For their intellectual and moral support I thank the following: my chair Dan Kammen for pushing me to finish this work and for providing mentorship and guidance throughout my unorthodox process; Lee Schipper for years of thoughtful conversation about how to be a good researcher and the deep importance of transportation data; my committee members Duncan Callaway and Betty Deakin for their support, advice, and willingness to step in after we lost Lee; Mike O'Hare and Anand Gopal for their chapter reviews and feedback; Kay Burns for helping me figure out the labyrinth of wrapping things up; Paul Friedman and the team at StreetLight Data for developing the most interesting transportation data on the planet; and my ERG family for the hours of conversation, cooking and friendship – Nate Aden, Judson Boomhower, Kristin Brainerd, Zoe Chafe, Lara Cushing, Jamil Farbes, Vero Jacome, Morgan Levy, Bessma Mourad, Alison Koppe Seel, Jo Seel, Imran Sheikh, Rebekah Shirley, Michelangelo Tabone, Valeri Vasquez, Maggie Witt, the rest of the entering class of 2009 and basically every other ERGie with whom I've been lucky enough to share a class or seminar.

And, as always, thanks to Mom, Dad and Drs. (!) Benjamin and Kerilyn Schewel.

1: INTRODUCTION: TRANSPORTATION BEHAVIORAL DATA AND GREENHOUSE GAS EMISSONS

1A: WHY TRANSPORTATION DATA?

In 2017, transportation became the largest single source of greenhouse gas emissions from the United States (Energy Information Administration, 2019). Globally, the 2014 Intergovernmental Panel on Climate Change (IPCC) report found that, without far more aggressive policies, “transportation emissions could increase at a faster rate than emissions from other energy end use sectors” reaching 12 Gt $CO_{2\text{-eq}}$/year by 2050 (Sims et al., 2014).

The overwhelming challenge of combatting these emissions is made far more difficult by the fact that so little is known about transportation behavior. In the IPCC’s chapter on transportation, they listed many data gaps including:

- A poor understanding of consumer travel behavioral generally, leading to a hampered ability to predict behavior,
- A lack of up to date data on adoption of new trends such as electric vehicles (EVs), shared mobility, and mode shift, and
- Lack of data about freight movement (Sims et al., 2014).

The US Department of Transportation (USDOT) identified major shortcomings of current transportation data nationally, including basics such as differentiation of travel patterns by demographics and any meaningful data on bicycle and pedestrian trends, to more cutting-edge topics like including uptake of Transportation Network Companies (TNCs). They found this data lack was inhibiting investment decisions in infrastructure and the ability to evaluate the impact of policies and investments on the environment (United States. Department Of Transportation. Bureau Of Transportation Statistics, 2018).

To use a cliché – if we can’t measure it, we can’t manage it. And transportation must be managed if we are to avoid the most catastrophic consequences of climate change. **I propose that better collection and application data is necessary to achieve reduction of transportation-related emissions. This “better collection and application” comprises taking advantage of new data collection techniques, and smarter implementations of old techniques.**

Happily, advances in technology make this more feasible today than at any time in the past. The costs of massive computing resources have gone down, the world is swarming with mobile devices like smartphones and connected cars collecting massive (if messy) amounts of data, and new techniques in data science and machine learning have emerged to help get clean answers out of all that data (in a privacy-appropriate manner). In some cases, these new techniques will displace older ones. In other cases, the old ways have inherent advantages. In other cases yet, fusing new and old techniques will yield the most productive results.

1B: A DATA-ORIENTED FRAMEWORK FOR MEASURING TRANSPORTATION’S CLIMATE CHANGE IMPACT

Transportation-related climate change impact falls into two categories: direct emissions from the combustion of fuels, and indirect emissions from vehicle and fuel production, land-use change, and road/infrastructure consumption and maintenance. In this section I propose a framework for the direct *and* indirect impacts, building on existing frameworks. My framework (laid out in Equation 4) is structured to align with available data collection techniques as it is designed to guide transportation behavioral data collection programs. My framework also emphasizes that freight is a *consequence* of personal consumption, and not a separate system, as it is often described. (In this dissertation, the term "freight" is widely construed to include all goods movement down to delivery options which may be done in the deliverer's private vehicle).

My data-oriented framework builds on existing frameworks: the well-known I-PAT equation (Ehrlich & Holdren, 1971), which has had a long history of amendment for more specific applications (see Chertow, 2000); the ASIF framework for transportation sustainability impact measurement developed by Lee Schipper and others (Schipper & Marie-Lilliu, 1999); and the framework proposed by Sager and others in 2011 for meeting transportation emissions reduction goals (Sager, Apte, Lemoine, & Kammen, 2011) which I will call the ERG framework.

In the I-PAT equation is a simple multiplication that highlights the importance of population growth, a critical point the authors were making in 1971:

EQUATION 1.1: I-PAT FRAMEWORK

$$Impact = Population * Affluence * Technology$$

In the ASIF framework, transportation activity (A), modal share (S), intensity of vehicle fuel and load factor (I), and fuel mix (F) have an interaction matrix that generate climate impact. The interactions are often complex or counterintuitive, and include indirect transportation emissions. This structure helped justify the recommendation for comprehensive policies and uncertainties the authors wanted to convey.

EQUATION 1.2: ASIF FRAMEWORK

$$Impact = [Activity] \cdot [Modal\ Share] \cdot [Intensity] \cdot [Fuel\ Mix]$$

In the ERG framework, the core factors of I-PAT and ASIF are restructured in a way that aligns with sets of mitigation policies. The factors in the first brackets represent technological solutions – improving the efficiencies and fuel used in our vehicles. The factors in the second brackets represent behavioral solutions – improving use of transit, having shorter trip lengths between key locations and reducing trip rates overall.

EQUATION 1.3: ERG FRAMEWORK

$$\begin{aligned} Impact = (&Carbon\ Intensity\ of\ Fuel * Fuel\ Intensity\ of\ Vehicle) * (Vehicle\ Occupancy \\ &* Average\ Trip\ Length * Trips\ per\ Year) \end{aligned}$$

Like all these authors, my framework simply manipulates the foundational I-PAT units to create distinct factors that I want to highlight. For Sager *et al*, (2011) and Schipper and Marie-Lilliu (1999) the focus was comprehensive policy; for Erlich and Holdren, it was population. I structure my factors to align with my focus – the importance of accurate, feasible data collection to both describe and manage changes in the transportation sector. For example the data collected from smartphones has a fundamental unit of personal miles travelled (PMT); thus, PMT is pulled out as a factor in my framework equation. I separate the direct and indirect impacts of transportation because that too more neatly aligns with available data. Lastly, the rise e-commerce, ride hailing, and delivery are making the interaction of freight and personal driving far more important and more complex. Thus, I create distinct terms to call-out this interaction. These interactions are now more feasible to measure with new data collection techniques.

EQUATION 1.4: DATA-ORIENTED FRAMEWORK TO MEASURE THE CLIMATE IMPACT OF TRANSPORTATION

$$I = i_1 * \sum_{p,f} (P * MT * VLF * VE * CD * i_2 * Ind)$$

Where:

- *I* is climate change impact for the region of interest, defined by the location of the people doing the traveling and consumption (for example, the US or Virginia or Asia).
- i_1 is the coefficient of interaction between person miles travelled in the region of interest and freight miles travelled locally and globally. As e-commerce, delivery, and stay-at-home options for entertainment—which trade off freight miles for personal miles— continue to rise, this currently unknown interaction becomes more and more important, and must be measured from many different angles.
- *p,f* are subscripts designating personal and freight versions of the following variables.
- *P* is the population of the region of interest, for both personal and freight
- *MT* is miles travelled. For personal travel this is person-miles travelled (PMT) per capita. For freight this is induced freight ton-miles travelled (TMT) per capita.
- *VLF* is vehicle load factor. For personal travel this is the number of people in the vehicle. The load factor for walking is zero. For freight this is tonnage moved in the vehicle.
- *VE* is the efficiency, measured in units fuel per mile (such as miles per gallon or miles per kilowatt hour) of the vehicles used for both personal and freight travel.
- *CD* is the carbon-equivalent density of the fuel used in the vehicles for both personal and freight travel, measured by the grams of $CO_{2\text{-eq}}$ emitted per unit of fuel consumed.
- *i2* is the coefficient that describes the amount of supporting infrastructure (e.g. vehicles, roads, lanes, fuel) produced, maintained, and transported to support the personal and freight transport, as well as the land use change caused by this activity. It is assumed that personal and freight transport have different coefficients.
- *Ind* is the indirect carbon impact of this supporting infrastructure (e.g. vehicles, roads, lanes, fuel) produced, maintained, and transported to support the personal and freight transport described before, as well as the land use change caused by this activity.

Throughout this dissertation, I will often review to VMT for either personal or freight sectors. This is the product of population, miles travelled per capita, and vehicle load factor as described in Equation 5:

EQUATION 1.5: VEHICLE MILES TRAVELLED (VMT)

$$VMT = P * MT * VLF$$

The following table shows the 'crosswalk' between the ASIF framework, I-PAT, the ERG framework and my data framework.

TABLE 1.1: CROSS-WALK OF DATA FRAMEWORK TO ASIF, IPAT, AND ERG FRAMEWORKS.

IPAT	Data Framework	ASIF Framework	Data Framework	ERG	Data Framework
(P)opulation	P	(A)ctivity	VMT	Carbon intensity of Fuel	CD
(A)ffluence	MT, as GDP is correlated with national miles travelled by people and goods. This is also captured, by VLF in a more complex way. The relationship between affluence and likelihood to bike or take transit is not linear, as it is impacted by urban density, etc.	(S)hare for modes	VLF (a pedestrian has a VLF of 0, a mode choice of 'bus' may have a VLF of 30).	Fuel intensity	VE
(T)echnology	VE and CD. Today, technology in the guise of ride sharing apps and shared micromobility and telecommuting also affects VLF and MT	(I)ntensity	VE and VLF	Vehicle Occupancy	VLF
		(F)uel mix	CD	Trip length * Trips per year	Together, MT

The "Matrix Interaction" component of the Schipper framework, and the conclusions of Sager *et al*, both emphasize an important insight for transportation no matter what framework is used – there is no path to success by pushing on only one of the levers of these equations.

To demonstrate data collection techniques applicability to every factor is beyond the scope of any one dissertation.

Guided by the previous frameworks which emphasize the importance of comprehensive approaches, in Chapters 3-7 I focus on data collection applications that measure several factors together, and engage with the ever-more-important interaction coefficients. Specifically, I explore:

- VMT from personal shopping and freight for retail, as this topic comprises miles travelled, population, and load factor. In addition this makes steps towards understanding and quantifying the complex interaction of freight and personal travel in the era of e-commerce;
- The adoption of electric vehicles. This technology simultaneously improves vehicle efficiency and the carbon density of fuel but may have negative consequences for personal miles traveled; and,
- Three lenses into the interaction between the direct impacts of transportation and the indirect impacts of transportation:

- **The transportation of fuel itself.** This builds on previous literature which has pointed out that the refining and distribution of fossil fuels, which in part derives from direct fuel combustion in transportation, can contribute a significant amount to total regional emissions (Mizsey & Newson, 2001).
- **The interaction between land-use and personal miles travelled per capita, in particular urban density and commute miles:** Land use change has been identified as a major cause of climate change (Intergovernmental Panel on Climate Change, 2019). Transportation and land use are intimately linked. However, increased PMT is usually described as the consequence of land-use change, not a driver of land-use change. Therefore, data about land use change will be used as an input, not an output of the data collection applications.
- **A general emphasis on VMT-reduction.** As noted in earlier frameworks in the literature, such as (Richardson, 2005) and (Garceau et al., 2013), VMT is a critical component of many of the broader indicators of sustainability: safety, congestion, environment, economics, and emissions. The reductions in VMT envisioned by my work could be seen to also mitigate indirect impacts of transportation.

The construction of the vehicles themselves is often cited as another component of impact, but this is outside the scope of this dissertation. As 99.6+% of miles travelled in the U.S. in 2017 are on roads ("U.S. Vehicle-Miles (Bureau of Transportation Statistics)," 2019), road transport is the assumed context for most of this dissertation – as opposed to air, boat, or rail—unless explicitly noted.

1C: MOVING FROM IMPACT FRAMEWORK TO METRIC AND DATA COLLECTION GOALS

It is important to define three key terms: "data", "metrics", and "behaviors" as they will be used in this dissertation.

- "Behaviors" are things people do, such as buy a car, commute to work, get Pad Thai delivered, or go shopping at the outlet malls in Napa. The goal of Metrics is to describe, measure, or shed light on behaviors, so that we can do a better job helping policies/cities/firms/citizens improve social and environmental outcomes.
- "Metrics" are quantitative or categorical outputs that describe a behavior. For example, "National VMT for Shopping" or "Annual Per Capita VMT for Shopping in California" or "Number of trips between Zone A and Zone B on a typical weekday." Metrics are derived from data, after applying normalization methods, various types of models, and related assumptions.
- "Data" are empirically collected information, for example, the raw results of a survey or millions of raw records from GPS devices. Data collection is the first step in creating etrics.

To move from our impact framework to concrete data collection goals, it is useful to take a step back and first look the impact's constituent behaviors. Then from these behaviors we move to the metrics that describe them. The rest of this chapter is taken up by this discussion. Chapter 2 describes the applicability of an array of data collection techniques to the behaviors and metrics described in Table 2, below.

Certain key individual *behaviors* that drive combustion emissions, and thus they should have *metrics* that measure them, and *data* techniques that allow the metrics to be calculated with reasonable accuracy and efficiency. These behaviors are:

1. VMT-Related Behaviors:
    a. Long term place choices
        i. Home location and work location
        ii. Other key locations (such as child's school)
    b. Short term place choices
        i. Frequency of out-of-home activities
        ii. Location of out-of-home activities
        iii. Decisions to displace activities with delivery, such as e-commerce (this impacts PMT, and may increase other people's or companies' VMT)
    c. Route Choices
        i. Route taken to locations and presence of "trip chain" between the places above
        ii. Drive Cycle of of the person or place such as heavy acceleration, include, etc.
        iii. Mode choice decisions (including carpooling) between all the places above
2. Vehicle choices: Fuel economy and fuel type of the vehicle used for the trips above.
3. Decisions to refuel with a lower-carbon density fuel for vehicles that can consume more than one fuel.
4. Consumption choices that induce indirect impacts (e.g. buying local vs. European wine).

Policy decisions influence the whole suite of choices available to the person doing the behaviors (is there a bus route available at all? Do zoning decisions allow grocery stores to be sited near my child's school?).

For each *behavior* I outline quantifiable *metrics* that capture it shown in Table 2. The metrics list is not exhaustive for each behavior.

TABLE 1.2: VMT'S CONSTITUENT BEHAVIORS AND EXAMPLES OF METRICS THAT MEASURE THEM

VMT Constituent Behavior	Example Metrics
Long-term Place Choices	
Home Location Choice	Home address, transit proximity to home, home price sensitivity
Work Location Choice	Work address, job type, income, commute distance, commute length sensitivity, education level
Third/Fourth Place Choice	Presence of children in household, school location
Short-term Place Choices	
Decision to do an activity	Activity preferences, disposable income
Decision of where to do the activity (which store to do to, etc.)	Activity location, mode accessibility to locations
Use delivery for activity	Availability, cost of delivery

Route Choices	
Path taken	Actual route chosen, familiarity of route (how many times taken before)
Trip Chaining	Actual trip chains, purpose of each leg, spontaneity versus planning for chaining
Mode Choice	Actual mode choice, impact of time/cost on mode preference
Drive Cycle	Personally or regionally specific driving characteristics of each mile travelled (speed, acceleration, etc.) that affect vehicle efficiency and fuel use

2: TRANSPORTATION BEHAVIORAL DATA COLLECTION TECHNIQUES

In this chapter, I review the current status quo of techniques to measure transportation behavior related to Person Miles Travelled (PMT). In order to assess them, I rely on the definition from Chapter 1 on what constitutes PMT-relevant behaviors, and their constituent metrics. I use this set of behaviors as a way to determine the usefulness of various types of transportation behavior measurement techniques. First, I review traditional techniques such as surveys, and move into cutting edge techniques including the use of GPS, smartphone apps, and cellular tower-derived data. I conclude that each technique has different strengths and weaknesses. Surveys, for example, can collect very rich data about intent. However, they are extremely expensive and have systemic biases. GPS and smartphone app/cellular data can cover millions of people quickly and cheaply, but can't get at questions of intention, commodity carried on board, or passenger count.

2A: HISTORY OF TRANSPORTATION DATA COLLECTION IN THE US

This chapter reviews the most common techniques to collect data about, and/or model transportation behavior. Centralized transportation data collection is itself a relatively modern concept. Table 2 gives a high-level timeline of major U.S. policies since WWII, at the national and state level, that have impacted the collection of transportation data at large scale. Many of these policies have had environmental concerns (often air pollution, not climate change) as a driving factor. The linkage between transportation data collection and environmental sustainability has a history at least 40 years long.

TABLE 2.3: MAJOR US POLICIES THAT HAVE AFFECTED TRANSPORTATION DATA COLLECTION SINCE WWII.

Date	Policy	Impact
1966	Department of Transportation formed	Created as part of Great Society. One of initial stated missions was to collect data at national level
1969	National Environmental Policy Act	Environmental assessment, which can include sprawl/induced driving demand, must be performed for all federal facilities.
1970	Clean Air Act	Required transportation planners to help meet air quality goals, in part by measuring or modeling air pollution from cars/buses/etc.
1976-1980s	Deregulation of Freight and Subsidies for Rail	This leads to plummeting of trucking costs, making ex-urban shopping centers cheaper to supply with goods. Rail bankruptcies lead to state take-overs/subsidies. Different freight data collection needs and practices emerge as a result.
1990	Clean Air Act Amendments	Metropolitan Planning Organizations must incorporate land use planning—leading to a still on-going discussion of how to model the interaction of land use and transportation. This results in a rise in formal discussions about techniques for transport modeling and the data needed to support them.

1991	ISTEA	Transport investments must be economically AND environmental efficient. This led to questions relating to data, such as how to measure/model the impact of telecommuting?
1998	TEA-21	Loosened land use planning requirements from ISTEA.
1991/2008	Oregon TPR, California SB375 & others	PMT reduction was made an explicit goal for state policies. Now discussions are on-going in certain states about how to baseline, measure, and apportion it.
[current]	VMT Taxes	OR, AZ and others are exploring a PMT tax (as opposed to gasoline or car taxes). This would require different PMT data collection techniques on an individual level.

Table 3 gives an overview of the traditional and new data collection techniques discussed in this chapter, as well as often-used transportation modeling techniques that could be either enhanced or displaced by better data collection. The table rates each data collection to create metrics for, and modeling technique's reliance on, components of PMT-related behaviors. I use the behaviors as the rows, as listing all the metrics would be cumbersome. A full circle means "very good" and a half-full circle means "acceptable or partial" collection of data that create many metrics associated with this behavior. Blank circles indicate no applicability to this behavior. While the focus is on PMT, I include non-PMT transportation behaviors because some collection and modeling techniques allow multiple types of transportation data to be collected or modeled simultaneously, an inherent benefit that should be taken into account. A discussion of each new metric and method (including explanation of acronyms and shorthand) follows.

2B: TRADITIONAL AND NEW BEHAVIORAL MODELING APPROACHES AND THEIR DATA NEEDS

Trends in transportation modeling influence the demand for new transportation behavioral metrics and need for collection of related data, and conversely the availability of new data influences the evolution of models. Likewise, political and cultural demands for certain types of change influence the models desired (or mandated!) across the nation (Bates John, 2007).

For example, in the early 1990s, a demand for transportation to be environmentally efficient increased the need for accurate PMT measurements and a demand to better understand how certain interventions (such as telecommuting) reduce PMT. In turn, this led to more focus on activity-based models and models that incorporate trip-tours, increasing the need for good data collection on trip purpose as well as trip chaining.

Likewise, the increase in vehicle efficiency from CAFE has led to a decrease in gas taxes, raising concerns about the fiscal health of programs that rely on gas taxes. To counteract this trend, some states have begun exploring a tax based on miles travelled. This requires more accurate collection of PMT for individuals, and modeling of future PMT under different paradigms (Starr McMullen, Zhang, & Nakahara, 2010).

Many in the literature have noted before that the new trends in modeling and new transport behaviors themselves mean the field is in sharp need of new data collection needs. I synthesize what has been said (mostly by Peter Stopher at the University of Sydney), focusing on the most relevant constituent behaviors for PMT.

New types of models (notably simulation, activity-based, and tour-based) have increased data demands on several relevant dimensions. First, many of the best applications require geo-tagged trip end points (or activities) down to precise latitudes and longitudes, not just counties or transportation-activity zones (P. R. Stopher & Greaves, 2007a). This pushes data collection to spatially-enabled technologies such as GPS and smartphone apps.

Second, several of the new models, notably activity-based, have arisen in response to the theory that transportation is and should be modeled as a demand derived from other activities, not an activity in itself. Early activity-based modeling was performed using only existing, survey-based sources. This sources, as discussed below, often had underreporting of short trips and omitted trips. Activity based modeling, it has been noted, is particularly sensitive to these types of omissions, leading to need for data collection techniques without this flaw (Veldhuisen, Timmermans, & Kapoen, 2000). More recently, the rise of activity-based concepts in modeling has led to more comprehensive and detailed category lists for trip purposes in household surveys, and time-use based diaries (as opposed to travel diaries) (P. R. Stopher & Greaves, 2007a).

Thirdly, new models, notably simulation models such as the UrbanSim model developed at Berkeley by Paul Waddell and colleagues, involve the integration of many data sets (mostly spatial) not previously required for transportation modeling. Examples include assessor parcel price data and information about vacancy, etc. (Waddell, 2002). This also increases the need for integration considerations between transportation data and the other data sets, including but not limited to geospatial tagging.

Fourth, activity-based models, simulation models, and tour models place increased emphasis on tours, instead of individual trips, as the key input for PMT and other metrics. In addition, the role of habits and values has become important in defining likely behaviors (Paulssen, Temme, Vij, & Walker, 2014), (Eriksson, Garvill, & Nordlund, 2008), (P. R. Stopher & Zhang, 2011). These trends both increase the need for accurate data capture of trips tours and travel habits indicating a need for data collection techniques that have persistent, unique identifiers for individuals or small groups of people for many days.

Fifth, all three new model types are "process models" as opposed to "outcome models" in the words of Peter Stopher. Thus, better collection of data about how people make decisions about travel is needed (P. R. Stopher & Greaves, 2007a).

Sixth, the costs of running surveys has gone up sharply, in part because the willingness of participants to fully fill out a travel diary or survey has gone rapidly down. This change in accessibility to respondents is due to several factors, including the rise of cellphones instead of landlines, and shifting attitudes about government data collection (P. R. Stopher & Greaves, 2007a). For example, the most recent 2018 National Household Travel Survey did not use professional interviewers, instead relying entirely on self-reporting as a cost saving technique. This has lead to wide-spread doubts about the usefulness and comparability of the data collected in this effort, even in official documentation (Lawson, 2018). In addition, the need for data collection frequency as gone up because new behaviors (TNCs, scooters, bike share) emerge rapidly. To even maintain previous levels of sampling for traditional modeling techniques at a reasonable cost, new more cost-effective and normally distributed techniques are needed.

Lastly, it is important to note—as others have before—the power of inertia in transportation modeling. The traditional models and data collection techniques have significant inertia behind them, ranging from the human capital inertia bound up in the skills and comfort zones of the analysts and regulators who work in transportation, to the infrastructure and capital inertia of the costs and equipment already sunk in modeling software and sensing devices, survey protocols, and more. The history of inertia in transportation modeling—for example the longevity of four-step modeling despite predictions of its demise as early as the mid- seventies (P. R. Stopher & Greaves, 2007a)—is strong enough that it should be kept in mind when evaluating the potential of new technologies. As I will discuss below, new data collection techniques that can at least partially be fit in as inputs to old models—both quantitative and mental— may gain traction faster than radical departures from the status quo.

2C: TRADITIONAL AND NEW DATA COLLECTION TECHNIQUES

In this section, I give a brief overview of each method of data collection, with a discussion of the strengths and weaknesses of each. Strengths and weaknesses are defined relative to the goal of the ability to measure and facilitate management of PMT.

2C.1 TRADITIONAL DATA COLLECTION TECHNIQUES: STRENGTHS AND WEAKNESSES

HOUSEHOLD TRAVEL SURVEYS

Household transportation surveys are the most prevalent data collection technique covering a broad range of transportation behaviors. The Bureau of Transportation Statistics has conducted The National Household Travel Survey (NHTS) since 1969 (though its title has changed over the years) on a semi-regular basis, between every five and ten years. In addition, many states and regions conduct their own household transportation surveys on a regular (though usually not annual) basis. Usually, modern Household Travel Surveys include requiring participants to keep transportation journals or diaries, in which they catalogue trips, trip time/distance, vehicle occupancy, trip purpose and more. Alternatively (or as a supplement), some surveys ask participants to recall travel behavior in the past as opposed to keeping a diary either via a professional interviewer, or as self-reporting.

The overwhelming strength of the travel surveys is the ability to ask questions and collect linked data about multiple facets of transportation behavior, ranging from vehicle occupancy to PMT to mode and trip purpose, in the same instrument. Some travel surveys include in-depth questions about preference and choice. In addition, household travel surveys allow researchers to carefully design and select a sample population, enabling accurate representation of a population (P. R. Stopher & Greaves, 2007a).

In particular, the NHTS is a nationally consistent data collection instrument, allowing comparisons between regions. The NHTS and its predecessors have also been reasonably consistent in terms of questions asked and data collection techniques, though the most recent 2018 update seems to have major flaws in this regard, still being explored (Lawson, 2018). This enables long-term longitudinal analyses of certain transportation behaviors going back 40+ years. Chapter 3 of this dissertation is an example of utilizing the strengths of traditional surveys, and the NHTS in particular, to explore and analyze shifts in transportation behavior—PMT related to shopping—in a historical context.

However, travel surveys have some weaknesses that have in part led to the proliferation of new data collection techniques in recent years. One major weakness is the high (and continually rising) expense and time-intensiveness of survey work (Hartgen, 2009). Not only is the survey burdensome for participants, it requires huge amounts of data entry and tabulation by research teams (P. R. Stopher & Greaves, 2007a). As a result, sample sizes are not always large (the NHTS in 2009, for example, had 25,000 households for the national sample, plus 125,000 households for regional "add-on" studies paid for by particular regions). Problems associated with low sample sizes are compounded recently by decreasing response rates (Wilson, 2004) and it has been noted that non-responding households are often large and/or house more intensive travel, leading to potential systematic underestimates of total national travel (National Cooperative Highway Research Program, 2008). In addition, this level of sampling, while adequate for accurate national or state-wide figure, prevents analysis at a more granular level, such as for neighborhoods.

Not only are the number of households sampled too low for many applications, but the number of days sampled is too low. Data collection only occurs on a few days for each household, and major surveys are only done every few years. This lack of frequent collection introduces skews and prevents longitudinal analysis, inhibiting detailed understanding of the impact of events such as weather or economic recessions, or the impacts of particular policies (Ortúzar, Armoogum, Madre, & Potier, 2011). For example, the 2009 NHTS collected data from April 2008 to April 2009, the pit of the Great Recession. The previous survey collected data in 2001. The next update came 10 years later in 2018, after recovery but also after the stratospheric rise of eCommerce and TNCs. It is difficult to disentangle actual, decade-level trends from shorter-term impacts of the Great Recession when comparing the 2001 to the 2009 and 2018 data.

Another weakness inherent in travel surveys is the fallibility of human memory and consistent interpretation of behavioral categories (is it "shopping" if you go to the mall to meet a friend?), leading to human errors in the input data. As a few studies have indicated, there are systematic biases in the household surveys based on these human errors. First, people tend particularly omit short trips (P. R. Stopher & Greaves, 2007a) (Bohte & Maat, 2009a). Omission of short trips is particularly dangerous to tour-level analysis of travel, as the short trips are key components of tour-based measurement, and of trip-chaining agendas.

Second, people tend to omit non-work travel. In 1995, the NHTS revised its methods for collecting samples. Specifically, the survey started using Travel Diaries, as opposed to asking respondents to recall travel from the previous week, and household "rostering." As a result, survey responses changed significantly between 1990 and 1995, increasing total trips, and hence VMT, by over 20%. Oak Ridge National Lab adjusted 1990 data in retrospect to capture changes as if the survey had been administered using 1995 methods. The researchers found that trips were underreported prior to 1995 in the shopping and family business categories more than the average, and more than work-related travel categories, demonstrating a systematic memory bias that underrepresents non-work driving (Hu, 2004, p. AS-12). While same day travel diaries mitigate this bias, they do not completely eliminate it.

In 2017, the NHTS again revised its techniques, eliminated prompted recall with interviewers and using only self-prompted recall. This has led to concerns with the accuracy and comparability of the data, such as the potential that this survey shows a over-reports the decline in household VMT – making it hard to disentangle the impact of eCommerce with reporting error (Lawson, 2018).

IN-ROAD SENSORS

In-road sensors include wire-loops, cameras with OCR, radars and other devices that count vehicles and measure the speed (and in some cases, other characteristics such as axle number) of vehicles on a particular road segment. The main strength of data collected from these devices is its accuracy, timeliness, and persistence. Some of these sensors, such as wire-loops, provide extremely accurate measurements of vehicle speed and vehicle count on a particular road segment with very good time resolution for many months and years. In addition, new types of in-road sensors can link to uniquely-identified vehicles via RFID sensors, usually those associated with automated tolling such as FasTrak in California, or EZ Pass on the East Coast. This enables the in-road sensors to measure travel time between points throughout the day (Klein, Mills, & Gibson, 2006).

Obviously, one benefit of using some of these types of devices is their dual purpose, such streamlining toll collection or signaling a light to turn green. However, they have two clear limitations: a) they only collect a small number of metrics (travel speed, vehicle count, and in some cases travel time and segment pairs); b) in-road sensors are often very expensive, especially the labor to install and maintain them. As a result they are usually only used on large roads, such as highways. In addition, the in-road sensors do not measure the decision process of people on the road.

Many municipalities have mobile loop sensors that are placed for a few days at a time at various intersections to gather total vehicle count and/or speed data, but this practice has the detriment of non-persistent sampling and thus, is not very accurate (Krile, Todt, & Schroeder, 2016).

PROBE VEHICLES

Probe vehicles demonstrate a transition from old to new data collection techniques. A probe vehicle is a vehicle that is driving about, collecting one or more streams of data and feeding it back to a centralized location. Probe vehicle collection works best for data needs where a very small sample is needed to get relevant data for the whole. Real time traffic speed provides the best case of such a problem. Studies have shown that very few probe vehicles are needed to get a useful map of real time speeds in a region, though of course this number varies based on population, amount and granularity of road segments covered, and desired time resolution (Srinivasan & Jovanis, 1996).

Other examples of probe vehicle projects include Google's StreetView data set of images for all Streets in the world (Anguelov et al., 2010). In addition, Google and Waze (now a component of Google) and other mapping firms such as TomTom and Tele-atlas have begun the use of probe vehicles to create and update road maps, leapfrogging the expensive manual documentation of roads (Patent No. WO/2010/023568, 2010).

The strengths of probe-vehicle data collection are clear: low-cost, persistent, and relatively accurate collection of data. Probe vehicles can collect and distribute information in a timely manner ranging from annual updates to near-real time. Much probe vehicle data collection leverages already installed and useful technology, such as smartphones with navigation apps, or freight trucks/taxis with fleet management GPS tools on board, thereby reducing cost.

The weaknesses of probe vehicles are similar to those of in-road sensors—limited metrics can be collected because of technical constraints, as well as limitation to metrics that do not require large or representative samples. However, as the availability of location-enabled devices explodes, probe vehicles have transitioned into the large scale, passive mobile device data collection techniques described in the following section, with a much broad range of applicable metrics. Like in-road sensors, the probes do not measure decisions or preferences of travelers.

MAJOR GAPS FOR TRADITIONAL TECHNIQUES

To summarize, the major gaps in the traditional techniques are:

- High expense
- Lack of persistence and low frequency of data collection over time (both over multiple years and throughout the year)
- Skewed representativeness (both for all types of people and types of trips)
- Need for more geospatial tagging to enable new types of models
- Need for more information about how and why people make travel choices

2C.2: NEW DATA COLLECTION TECHNIQUES: STRENGTHS AND WEAKNESSES

This section introduces the several novel types of transportation behavioral data collection all enabled by the explosion of mobile devices (smartphones and connected vehicles) in the last decade. Next, I discuss the strengths and weaknesses of each type of data collection in the context of PMT and its constituent behaviors.

PERSONAL GPS TRAVEL DIARIES

Many groups have been exploring and improving upon the use of dedicated GPS devices as a means of supplanting or supplementing travel diaries. In addition, such devices are being deployed to support usage-based insurance programs (UBI).

GPS-enabled surveys have the benefit of being automatic, recording exact trip distances, endpoints with automated latitude and longitude, and times (e.g. (Jean Wolf, Guensler, & Bachman, 2001) (McGowen & McNally, 2007)). One of the first benefits of these studies was to reveal and better quantify the biases in human memory that affect all diary-based surveys.

Most GPS-enabled surveys thus far just supplement diary data from the participants (Bohte & Maat, 2009a), (J. Wolf, SchöUnfelder, Samaga, Oliveira, & Axhausen, 2004), (Caltrans, 2012). While the GPS enabled surveys can enhance richness and accuracy of results, as found in the literature cited above, work remains before GPS without participant interaction can totally supplant surveys. For example, several researchers found they had trouble correctly inferring trip purpose because of a lack of available geospatial data about land use (Peter Stopher, FitzGerald, & Xu, 2007). In addition, current GPS approaches tend towards the use of a specialized GPS recorder in the participants' vehicle, necessitating a lengthy recruitment and provisioning process for each survey. This raises the costs of persistent data collection.

Other researchers have been exploring techniques to mitigate these shortcomings. For example, several researchers have begun to use components in Smartphones to deduce travel mode either through location and time alone (Bohte & Maat, 2009a) or enhancing data streams with accelerometer data (Reddy et al., 2010). In addition, as noted by many researchers, contextual data about land use is increasingly available—though sometimes at a fee out of reach for most academic projects (McGowen & McNally, 2007) (Waddell, 2002).

Personal GPS data is a powerful option to replace highly detailed travel diary or questionnaire, when that data will be used at an individual level (for example – to teach the individual user about their own driving techniques) (Froehlich et al., 2009), (Soleymanian, Weinberg, & Zhu, 2016).

In summary, GPS diaries have been technique to improve shortcomings of travel diaries for population-representative data, but is not yet a radical alteration of data collection. This has obvious shortcomings—as diaries are still necessary, the same limitations of cost, sample size, frequency, and persistence still apply. However, they offer an exciting option when the goal is individual-level data.

MASS GPS DATA FROM CONNECTED CARS

Connected Car GPS data is data from the navigation equipment (often aftermarket) in personal and commercial vehicles. It uses GPS technology and thus is very spatially precise (5m or less). This data tends to have a relatively small sample size (compared to cellular options discussed below), and be biased towards newer-model cars and commercial trucks which may travel at different speeds than cars (S. M. Turner & Koeneman, 2018).

These biases do not matter for accurate collection of speed on a road segment with several vehicles and thus this source of data has quickly become the widely adopted preferred technique for speed and travel time management with many commercial providers. The FHWA also sources a large data set about speed derived from mass GPS data, which has been the subject of multiple studies for validation, and utilized in many applications (Bitar, 2016). The sample size is generally small, and in most available data the anonymized identifier of the device does not persist. Both these characteristics make statistical normalization difficult (StreetLight Data, 2019).

One of the benefits of this data is that it often is explicit about being sourced from commercial trucks. This has enabled dozens of conference, academic, and industry studies and projects about commercial truck patterns, from speed to routes, modeling, origins and destinations, parking and more (Flaskou, Dulebenets, Golias, Mishra, & Rock, 2015), (Gingerich, Maoh, & Anderson, 2016), (Pinjari et al., 2014).

MASS PASSIVE DATA FROM CELLULAR TOWERS

Literature has emerged in the last several years, pointing to the applicability of using cellular archival data for large-scale transportation analyses, notably to create the Origin-Destination matrices on which most regions transportation demand forecast models rely (e.g. (Zhang, Qin, Dong, & Ran, 2010) (Caceres, Wideberg, & Benitez, 2007)). Several companies have emerged to apply this technique as consultants for regional governments throughout the US, such as the Southern Alabama Regional Planning Commission (Harrison, 2012) or California (Milam, Stanek, & Jackson, 2012). Beyond this use case, not much exploration has occurred in applying this type of data to transportation problems outside of demand modeling (much has been done with regards to epidemiology), with the exception of some discussion of cellular data use for VMT taxes (B. Davis & Donath, 2012).

The overwhelming benefit of this approach is that it has a drastically higher sample size than personal GPS or survey methods. In addition, since the data is archival and anonymous, this large population can be analyzed and re-analyzed at times in the future at very low incremental cost per person. This improves the comprehensiveness and statistical representation of the data compared to the alternatives (Technology, National Cooperative Highway Research Program, Transportation Research Board, & National Academies of Sciences, Engineering, and Medicine, 2018).

However, cellular data as used thus far has three significant drawbacks. First, its geospatial accuracy is poor (~0.25 to 0.5 km) compared to GPS assisted GPS (aGPS) techniques discussed below. Second, data is collected infrequently, leading to missed trips and waypoints. These factors limit cellular data's applicability to very precise transportation measurements, such as routes taken, turning ratios and lane switching behavior, especially in spatially dense urban environments. In addition, because the data is anonymous, all information about users' demographics must be inferred from area demographics (Technology et al., 2018).

MASS PASSIVE DATA FROM SMARTPHONE APPS

Smartphone apps also collect locational data through a variety of techniques. These include GPS (using the phone's GPS chip), Wifi and Bluetooth proximity data, and other "GPS Assist" techniques. This means the devices are more spatial precise than cellular tower data. The GPS on a modern smartphone is usually better than 2m spatial precision 12/2/19 10:15:00 AM and the overall mix of sensors has been shown to have an average spatial precision in urban environments of 30m (PlaceIQ, 2016). Notably, most data points register the spatial precision as high, medium, or low. This allows users to filter by spatial quality (PlaceIQ, 2016).

When apps are open and being used by the phone end user, many collect data at a regular cadence. Even when apps are not open in the "foreground," with proper settings and user permissions, they can continue to collect locational data occasionally or as often as every 1-3 minutes (Lee & Sener, 2017). The total sample size of locational smartphone app data in theory is the same as the penetration of smartphones (over 100%). However, only some apps perform spatial data collection the data must be licensing and aggregated. Leading providers, such as those providing data used later in the dissertation, have 20+% of the population (StreetLight Data, 2019).

All these indicate that the smartphone app data is an alternative to data derived from cellular towers, which also has a large sample size but lacks spatial precision and pings infrequently making smartphone data a better alternative for personal travel studies of most types. Unsurprisingly, this source of data has begun to overtake cellular-tower derived data in academic and industry presentations and publications ((Lee & Sener, 2017), (Sheppard et al., 2019) (Bernardin & Sadrsadat, 2018)).

MAJOR GAPS FOR NEW DATA COLLECTION TECHNIQUES

The types of new data collection techniques I describe in this section have some complementary strengths and weaknesses, as described in Table 4.

TABLE 2.4: THE RELATIVE STRENGTHS AND WEAKNESS OF NEW DATA COLLECTION TECHNIQUES.

	GPS – Personal Diary	GPS – Navigation	Cellular Tower	Smartphone App
Low cost (if initially collected for other purposes)		●	◐	●
Persistence			●	●
Geospatially Tagged	●	●	●	●
Documentation of choice processes	●		◐	◐
Spatial Accuracy	●	●	◐	●
Sample Size			●	●
Sample Less Biased, Possible to Normalize			●	●
Frequency of "pings"	●	●		◐
Able to be to certain demographics, modes, etc			●	●

In the following table I compared the traditional and new data collection techniques (bundling navigation GPS, cellular tower, and smartphone data into one column) in how they can address the concerns of PMT measurement, raised in an earlier section.

TABLE 2.5: TRANSPORTATION BEHAVIORAL DATA COLLECTION TECHNIQUES, RATED BY THEIR ABILITY TO CAPTURE IMPORTANT METRICS

A full circle means "excellent ability to collect" and a half circle means "some ability to collect." an empty cell means no application to the metric.

Category	Traditional Data Collection			New Data Collection	
Method / Metric	Household Transportation Surveys	In-road sensors	Probe	GPS Diary Enhancement	Big Mobile Device Data Collection
Long-term place choices:					
Home Location (and trips to/from it)	●			◐	●
Work Location (and trips to/from it)	●			◐	●
Other Favorite locations	●			◐	●
Short-term destination choices:					
Number of activities	●			◐	●
Location of activities	●			◐	●
Use delivery in lieu of activity	●				◐

Route Choices					
Paths taken				●	●
Trip Chaining aka Tours*	◐			●	●
Mode Choice	●			●	●
Drive Cycles			●	●	
Other Useful data not explicitly part of PMT					
Trip Volume by Road / Region		●			●
Speed/Traffic		●	●		●
Before/After Studies					●
Safe Driving				●	
Non-Vehicular Travel	●	◐			●

2D: DATA COLLECTION TECHNIQUES USED IN THIS DISSERTATION

There are elements of almost all the data collection techniques discussed above used in the various analyses presented in this dissertation. More detailed methods about the metrics created from this new data are available in each relevant chapter, but it is useful to summarize the key elements and notable differences from/additions to the relevant literature here.

Chapters Three and Four provides an example of analysis done using the traditional data collection techniques, notably Household and Commercial Travel Surveys, to explore changes in PMT related to shopping and retail freight since 1969, as well as freight for fuel transportation. They demonstrate and take advantage of the key benefits of traditional techniques: that they go back in history, that they collect clearly stated trip purposes, vehicle occupancies, demographics (including gender, an important demographic but particularly difficult to deduce from the new data collection sources), trip distances, chaining behavior, commodities logged, and more. As it turns out, these benefits are critical: the historical trends of the past 40 years allow behavioral insight that would not have been possible with a shorter term study, and gender dynamics are key to understanding the behaviors at hand.

However, the analysis in Chapters Three and Four also highlights some of the key limitations of survey-based analysis. The fact that data was only collected every five to ten years severely limits the analysis, such as limiting the exploration that can be done on the impacts of the Great Recession. In addition, fallibilities in human memory are especially pronounced in short trips, trip chains, and non-work related trips, all of particular importance to this study.

Chapters Five lays out theoretically, and then Chapter Six demonstrates via case study in India, how personal GPS diary devices can be used to log detailed data about individual trips. It demonstrates the key benefit of this data – highly individualized characteristics. Taking the example of vehicle electrification, this chapter demonstrates two ways such granular data is important: in one example, such data to give feedback to an individual to influence their car buying behavior. In the second, the granularity found with this new data collection techniques reveals the importance of highly localized policy making and emissions modeling based on driving patterns in different cities.

Chapter Seven uses the emerging technology of mass amounts of locational data, collected passively via Smart Phones, exploring how urban density at home and work interacts with total, work-related, and non-work-related miles driven. This demonstrates the great strength of this type of data – massive sample size combined with high spatial granularity and longitudinal data collection. This enables the analysis at statistically meaningful scale of patterns across many geographies, individuals, and times of year. Thus, this data can shed light on questions about the relationship of density and miles travelled which previously have not been answered conclusively due to data constraints

3: SHOP 'TILL WE DROP: A HISTORICAL AND POLICY ANALYSIS OF RETAIL GOODS MOVEMENT IN THE U.S.

CHAPTER 3: PREFACE

In the following chapter, Professor Lee Schipper and I use traditional data techniques to measure the rise of personal VMT for shopping as well as the rise in retail-oriented freight. This work is published verbatim under the same title in Environmental Science & Technology (Schewel & Schipper, 2012), with minor edits to adapt the formatting to match other chapters. Due to Dr. Schipper's sad and untimely passing, I cannot reproduce it here with his explicit consent. However, the committee and I are certain he would have gladly given such consent.

CHAPTER 3: ABSTRACT

The movement of retail goods is central to modern economies and is a significant—but understudied—fraction of our overall energy footprint. Thus, we propose a new category for energy analysis called Retail Goods Movement (RGM) that draws its boundaries around the portion of freight dedicated to retail goods and the portion of driving dedicated to shopping. Historically, the components of RGM have not enjoyed policy priority. However, the net payoff from energy research and policy directed at RGM may now be high enough relative to other options to deserve increased investment. We combine a quantitative decomposition of the dynamics of RGM energy use with a qualitative discussion of what trends could have contributed to them. The RGM sector's energy use grew from 1.3EJ (2.8% U.S.) in 1969 to 7.0 EJ (6.6% U.S.) in 2009. The major drivers were increases in: population, freight tonnage (before 1990), distance freighted per tonne and driven per shopping trip (after 1990), and weekly shopping trips per household (before 1995). RGM energy intensity increased per capita (180%), per constant dollar GDP (60%) and per retail expenditure (140%). Finally, we describe policy recommendations that could become the basis of a sound RGM resource plan.

3A. INTRODUCTION

The traditional division of the transportation sector into two subsectors—personal transport and freight transport—masks connections between the two. For examples of this division, see the chapter organization of the Transportation Energy Data Book , or recent research on the global climate impact of transportation (Borken-Kleefeld, Berntsen, & Fuglestvedt, 2010). Yet, the same act of consumption increases the likelihood of both an individual round trip to the retail outlet and a chain of freight shipments to restore the inventory of the retail node (see Figure 1). As shown in Figure 2, we find it more revealing and useful to quantify this overlap between the two sectors, which we call "Retail Goods Movement" (RGM).

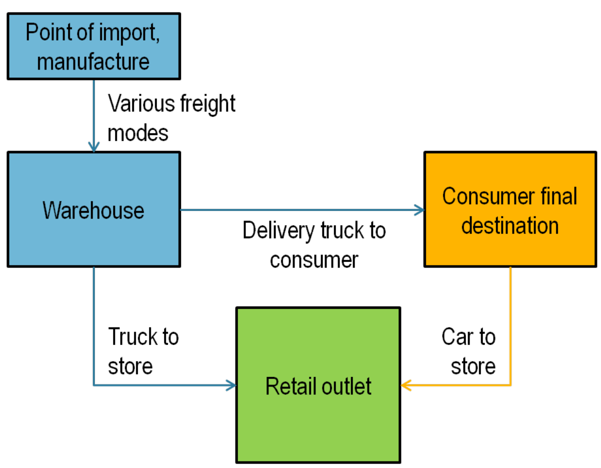


FIGURE 3.1: SCHEMATIC DIAGRAM OF THE FLOW OF GOODS FROM POINT OF MANUFACTURE/IMPORT TO THE CONSUMER.

Transportation (represented by arrows) occurs on the freight side and on the personal side of the retail outlet.

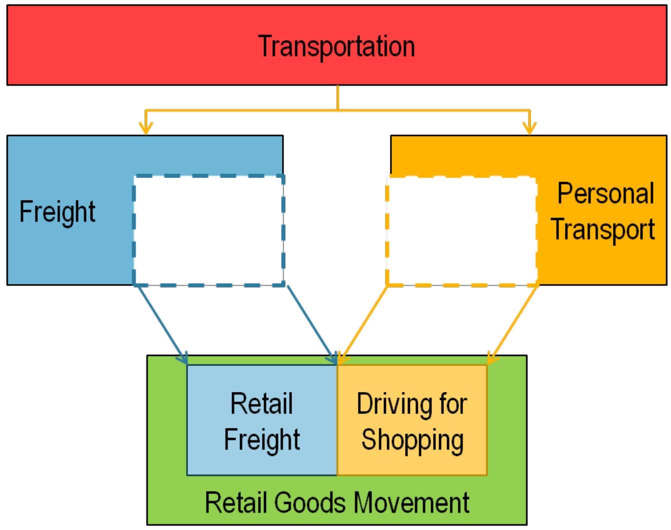


FIGURE 3.2: RECLASSIFICATION OF THE TRADITIONAL CATEGORIES OF FREIGHT, PERSONAL TRANSPORTATION, AND OVERALL TRANSPORTATION FIT INTO A RETAIL GOODS MOVEMENT (RGM) FRAMEWORK.

In the past, the separate components of RGM have not enjoyed policy priority. U.S. transportation energy policy has focused on individual driving instead of freight (Transportation Research Board, 2010). Now freight is the fastest growing category of energy use in the transportation sector and one of the fastest in the U.S. (Schipper, Saenger, & Sudardshan, 2011). Similarly, most transportation policy affecting personal transport has historically focused on commuting (Transportation Research Board, 2010), but driving for commuting is shrinking as a percent of kilometers (km) driven in favor of shopping and social/recreational trips (Oak Ridge National Laboratory, 2009).

RGM energy use is increasing faster than even aviation energy use: since 1969, RGM's energy use has increased 440% compared to aviation's 70%. Aviation energy use contributed 2.2% of US total energy use, while RGM accounted for 6.6% in 2009 (S. C. Davis, Diegel, & Boundy, 2011). And yet, aviation's energy and climate impact has received significant attention (Penner, 1999) (European Union, n.d.).

As we show in this paper, The RGM sector's energy use grew from 1.3EJ (2.8% U.S. total) in 1969 to 7.0 EJ (6.6% U.S. total) in 2009. These figures translate to just over 6% of the US total greenhouse gas emissions (Environmental Protection Agency, 2010). In the decomposition analysis, we explore the factors which contributed quantitatively to that increase. Table 1 shows which of these factors were most responsible for the growth in RGM energy use, and contextual explanations. Overall, retail freight contributed ~70% of the increase in RGM energy use.

TABLE 3.6: SUMMARY OF THE KEY CONTRIBUTORS TO THE 440% INCREASE IN RETAIL GOODS MOVEMENT ENERGY USE BETWEEN THE LATE 1960S AND 2009, FROM 1.3 EJ TO 6.9 EJ.

Factor	Explanations
Key quantitative contributors to increases in the componenets of RGM	
Increased energy use for driving-for-shopping, late 1960s to late 1980s	• Increase in population • Increase in weekly shopping trips • *Mitigated by improved MPG resulting from CAFE legislation
Increased energy use for driving-for-shopping, 1990 to 2009	• Increase in population • Increased distance per shopping trip
Increased energy use for retail freight, late 1960s to late 1980s	• Increased tonnage (per capita and per retail dollar)

Increased energy use for retail freight, 1990 to 2009	• Increase in distance shipped per tonne • Increase in energy intensity per tonne-km
Proposed qualitative explanations for contributing factors	
More frequent shopping trips per capita and per household, 1969-1995	• Expansion of the utility of shopping (shopping for fun, relaxation, exercise) • Increase in women in the workplace and related fragmentation of household organization (41% of women worked in 1969, up to 59% in 1995) • Move to fresher foods and more frequent grocery shopping (eg 27% increase in fresh fruit sales compared to 2% increased in preserved in the relevant time period)
Increase in kms / trip, 1990-2009	• Fewer retail stores density from ~9 per 1000 people to ~4 per 1000 people • Segregation of residential and commercial areas
Increase in retail tonnage, 1967-1987	• Increase in consumption of goods per capita, overcoming a decrease in the mass density of a dollar of retail goods, from $4550/capita in 1967 to $6840/capita in 1987 (measured in 2007$).
Increase in distance shipped / tonne, 1967-2007	• Deregulation driving down the costs of trucking a tonne-km from by 12% to 77% per tonne-km depending on truckload size. • Increase in share of retail goods that are imported
Increase in energy intensity / tonne-km for retail freight, 1967-2007	• Deregulation driving down the cost of trucking compared to rail and barge leading to some modal shift • Just-in-Time delivery trend favoring trucks over rail to barge

All these factors suggest that the net payoff from energy research and policy directed at RGM may deserve increased investment. In the body of this paper we:

- Define and develop the new category of transportation services: “Retail Goods Movement” (RGM),
- Calculate and decompose the energy used for RGM and the change in that energy use for the past 40 years in the U.S. to reveal contributing factors,
- Trace the history of both qualitative and quantitative indicators that account for the changes observed in the factors, and
- Suggest policy approaches that can slow and reverse the increase in RGM energy use.

Energy-related policy that addresses the RGM will have features distinct from other transportation energy policy, and addressing RGM as one integrated sector will have priorities different from energy policy that addressed to each component separately.

3B: EXISTING LITERATURE

Our work builds on and extends existing literature that has addressed separate elements of RGM, and/or has developed the use of decomposition as a technique to understand energy changes over time.

3B.1: LITERATURE ABOUT DRIVING-FOR-SHOPPING

In 2004, Hu performed a detailed study of change in US driving behavior which looked past editions of the National Household Travel Survey to measure change in driving habits (Hu, 2004). We use the same source. However, whereas Hu only looked back to the 1995 study, we start in 1969. Hu did not explore the energy implications of the longitudinal behavioral changes, which is the focus of our paper.

Several works have indicated that proximity is not the only determinant of retail store choice for consumers (Finn & Louviere, 1996) (Fotheringham & Trew, 1993). This literature challenges some theories of retail geography, including central place theory, which found a more clear relationship between proximity of consumer home to the retail and likelihood of purchase at that retailer (eg (Berry, 1967)). This can also be seen as an extension of Alderson's "dynamic" theories of heterogeneity and retailer differentiation (Alderson, 1965). Modern researchers have begun to point out the energy implications of this: For example, Handy et al found that residents of "new urban" communities with walkable shopping did not necessarily use the nearby stores, while residents from other neighborhoods drove to the "walkable" retail district (Handy & Clifton, 2001). Cervero found in 2006 that mixed job/residential development reduces vehicle km travelled more than does mixed retail/residential development (Cervero & Duncan, 2006).

3B.2: LITERATURE ABOUT RETAIL-DRIVEN SHIFTS IN FREIGHT

Freight as an energy-using sector has a notably poor literature and policy history, as noted by the Transportation Research Board (Transportation Research Board, 2010, p. 67). Schipper et. al. did the most comprehensive analysis of the drivers behind changes in freight energy use in the U.S. in 1992, updated in 2011. These studies did not delve into the role of retail goods compared to other goods. Vanek and Morlok, in two papers (1998 and 2000) do delve into freight energy use by commodity, and broke freight down into more granular categories than we do (such as food) (F. Vanek & Morlok, 1998), (F. M. Vanek & Morlok, 2000). While such granular analyses is valid for many purposes, we chose to aggregate all retail goods together because the transportation of such goods has much in common (compared to, for example, freighting of coal), and can be affected by common policy levers. Vanek and Morlok also do not extend the analysis to driving for shopping.

3B.3 LITERATURE ABOUT THE CONNECTIONS BETWEEN DRIVING-FOR-SHOPPING, FREIGHT, AND E-COMMERCE

In a foundational work for freight-driving connection in 1994, McKinnon and Woodburn remarked: "…when assessing the environmental impact of retailing operations, it is important to regard the supply chain as extending as far as the customer's home" (A. C. McKinnon & Woodburn, 1994, p. 125).

Since then, the work that most directly relates to RGM addresses the energy implications of on-line shopping. However, while catalogue and on-line commerce has seen a tenfold increase since 1969, the same cannot be said for energy and environmental literature related to it. The few relevant studies tend to take the form of life-cycle assessments (LCAs) comparing the energy impact of delivering a product by going to the store, or by on-line shopping. Matthews et al (2001) and Fichter (2002), reviewing impact assessments for books and groceries respectively, found that on-line shopping could reduce total transportation energy associated with the good by between 0% (breakeven) and 35% (Fichter, 2002) (Matthews, Hendrickson, & Soh, 2001). McKinnon et al found that savings could be as high as 95%, under the right conditions in the UK (Edwards, McKinnon, & Cullinane, 2010). These conditions include being sure that the delivered good is actually displacing a trip to the store and that the package is delivered on the first trip. However, in a case study on electronics, Weber pointed out that if e-commerce causes goods to fly on planes then it is the less environmentally friendly option (Weber et al., 2009).

3B.4: LITERATURE ABOUT DECOMPOSITION ANALYSES FOR LONGITUDINAL NATIONAL ENERGY STUDIES

Our approach builds on a body of literature that uses decomposition techniques to analyze changes in energy use in large sectors of national economies across time (Yamaji, Matsuhashi, Nagata, & Kaya, 1991). The Kaya Identity multiplies population, energy intensity, and activity (shown in the Kaya Identity as gross world product, and here as trips and shipments) to measure a composite measure of impact called F. Analysts can then index both F and its constituent components to evaluate the relative importance of each component. The Log-Mean Divisia Index (LMDI) is a similar approach to Kaya. However, it is used when the factors are additive, in order to eliminate residuals (Ang, 2005). Our integration of decomposition with contextual historical data, cultural trends, and policy implications draws on *Raupach et al* (*15*). Like Raupach, we use ratios to explain how components of the decomposition relate to each other. Unlike Raupach, we also use ratios between the decomposition factors and economic markers.

Some researchers have already applied decomposition techniques to transportation. Schipper published several studies which use decomposition to explore the increase in national transportation emissions in the U.S. and abroad, and to project energy use into the future (Schipper et al., 2011) (Schipper, Scholl, & Price, 1997) (Kamakaté & Schipper, 2009). Steenhof et al (Steenhof, Woudsma, & Sparling, 2006, p. 370) used the same technique to understand and project the increase in Canada's emissions from freight. Schipper and Steenhof noted that freight's share of both nations' energy and emissions bill would continue to rise without policy and technical change. Our study shares methodologies with these studies and follows Steenhof and Schipper's lead in deep investigation of components of the freight sector's energy consequences.

3C: METHODS AND DATA

We organize data from publicly available data sources through the lens of "retail goods." We have extracted data from older data sets, and standardized these data across years so as to facilitate comparison. This data set is both novel and useful to other researchers and further information about the set and our manipulations of it is available in the supporting materials section.

3C.1 DRIVING-FOR-SHOPPING

The impact of driving-for-shopping is measured by Joules for driving-for-shopping (J_{DFS}), the product of Vehicle Kilometers Travelled for Shopping (VKT_S) and energy intensity of each km. We decomposed VTK_S into five factors (see Equation 1). We chose factors which were policy-relevant and available from the National Highway Travel Survey (NHTS) for the sake of data consistency (Oak Ridge National Laboratory, n.d.).

EQUATION 3.6: VKT FOR SHOPPING

$$VKT_S = USpop * \left(\frac{people}{household}\right)^{-1} * \frac{person\_shopping\_trips}{household} * \frac{vehicle\_shopping\_trip}{person\_shopping\_trip} * \frac{km}{trip}$$

Next, we calculated the gallons of fuel burnt for driving-for-shopping by multiplying VKT_s by the weighted average fuel efficiency of the on-road fleet in gallons per kilometer (GPK, see Equation 2) in the appropriate year (Energy Information Administration, n.d.). Equation 3 shows how the results of 1 and 2 are combined to get J_{DFS}. We assume that all fuel was gasoline.

EQUATION 3.7: FUEL USE FOR DRIVING-FOR-SHOPPING

$$\frac{gallon}{km} = (km_{PC} * \frac{gallons}{mile_{PC}} + km_{LT} * \frac{gallons}{mile_{LT}}) / (km_{PC} + km_{LT})$$

EQUATION 3.8: JOULES FOR DRIVING-FOR-SHOPPING

$$J_{dfs} = \frac{\overline{gallon}}{km} * VKT_s * \frac{J}{gallon}$$

We indexed all the values in Equations 2 and 3 to 1990 for driving or 1987 for freight. We chose these years because a) both sectors experienced significant shifts around those times which are better visualized by the central index and b) data were collected for 1990 for driving and 1987 for freight and using the same index year for both would require extrapolation of one or the other category.

Finally, we performed a literature review of historical, sociological, and business literature to look for qualitative information that could create an explanatory narrative around the most important ratios.

3C.2: RETAIL FREIGHT

We used analogous methods for freight analysis. Retail freight (RF) activity is measured in Vehicle Tonne Kilometers Travelled ($VTKT_{RF}$) shown in Equation 4 and energy use in Joules for retail freight (J_{RF}), shown in Equation 5.

EQUATION 3.9: VEHICLE TONNE KILOMETERS TRAVELLED FOR RETAIL FREIGHT

$$VTKT_{RF} = \frac{avg.km}{trip_{RF}} * \frac{tonnes_{RF}}{year}$$

EQUATION 3.10: JOULES FOR RETAIL FREIGHT

$$J_{RF} = \sum_{i=1}^{5} \sum_{j=1}^{16} VTKT_{i,j} * (\frac{J}{VTKT})_j$$

In Equation 5, "i" represents the mode of transportation (i = 1 means railroad, i = 2 means truck, etc.), "j" stands for class of retail freight (j = 1 means textiles and leathers, etc).

3C.3: COMBINED RGM

Combining the two sets of data into one presents a few hurdles. First, the data sets do not draw data from the same years. We took a simple approach to this problem, extrapolating linear growth for each variable between each pair of contiguous observation years in the data set.

Because the RGM energy use was derived from additive factors, as shown in Equation 6, we used an LMDI decomposition (see methods). The effect "D" for a given variable is calculated as shown in Equation 7.

EQUATION 3.11: JOULES FOR RETAIL GOODS MOVEMENT

$$J_{RGM} = J_{RF} + J_{DFS}$$

EQUATION 3.12: LDMI DECOMPOSITION

$$Dx,i = \exp\left(\sum_i \frac{L(V_i^T, V_i^0)}{L(V_{total}^T, V_{total}^0)} \ln\left(\frac{x_{k,i}^T}{x_{k,i}^0}\right)\right)$$

x_k is a variable (eg x_1 equals US population), *i* is a sub-category (i = 1 is driving, i = 2 is freight), V is the output of total energy use, T = 0 is the base year, and T is the year in question. L (a,b) = (a-b)/(ln*a*-ln*b*).

3C.4: DATA

Our earliest driving data is from 1969, while our earliest freight data is from 1967. Therefore, all driving indices, and all combined RGM indices start at 1969, while the freight indices start in 1967. All dollars are measured in $2007 and inflated using the consumer price index (CPI). Table 2 summarizes the data sources, benefits, and detriments of the sources. A detailed discussion of the data sources and any manipulations made to the data is available in the supporting materials.

TABLE 3.7: DATA SOURCES, YEARS AVAILABLE, AS WELL AS KEY BENEFITS AND LIMITATIONS OF EACH SOURCE.

	Driving for Shopping	**Retail Freight**
Data source	National Household Transportation Survey (Oak Ridge National Laboratory, 2009)	Commodity Flow Survey (US Department of Transportation, Bureau of Transportation Statistics & US Department of Commerce, US Census Bureau, 2006) (US Census Bureau, 1970)
Years available	1969, 1977, 1983, 1990, 1995, 2001, 2009	1967, 1972, 1977, 1982, 1987, 1992, 1997, 2002, 2007
Benefits	Nationwide sample, relatively constant categorization and historical reach.	Regular surveys, nationwide sample, use of NAICS codes
Limitations	Slight shifts in categorization, lack of statistical markers in earlier sets (such as sample size), sporadic sampling gaps (five or more years) and poor data formatting and usability for earlier years	Shifts in NAICS codes, poor data formatting/availability for early years, no explicit tracking of empty backhauls

Historical data about the average kilometers per gallon of vehicles and energy content of fuel was available from the Transportation Energy Data Book series (S. C. Davis et al., 2011), Annual Energy Reviews (Energy Information Administration, 1999), and the Environmental Protection Agency (Environmental Protection Agency, 2005).

For the freight analysis, we used the two-digit codes from the Standard Industry Classification (SIC) and North American Industry Classification System (NAICS) to include and exclude categories of freighted goods based on whether those goods went to retail final destinations or not. To make this decision, we relied on descriptions of classifications in the CFS. Energy intensity data for freight modes in specific years was taken from appropriate editions of the Transportation Energy Data Book (S. C. Davis et al., 2011). More details can be found in the supporting material.

Our category for freight only includes freight that moves within the borders of the United States. Thus for imports, movements to the border of U.S. and movement within the country of production are excluded. Exploring these "imported" and "exported" freight emissions is beyond the scope of this paper, but will be integrated in the future, building on emerging research on this difficult-to-track topic. For example, Davis and Caldeira found that the transport emissions exported by the U.S. (fuel burned here for goods consumed elsewhere) about equals the transport emissions imported (transportation elsewhere for goods consumed here) (US Census Bureau, 1970). Yet Steenhof et al found that one of the top causes of freight emissions increase in Canada was cross-border movement with the U.S. (Steenhof et al., 2006). We discuss the impact that rising imports have on domestic freight movements later in the paper.

3D: RESULTS AND CONCLUSIONS

3D.1: RESULTS

RGM sector's energy use grew from 1.3EJ (2.8% U.S. total) in 1969 to 7.0 EJ (6.6% U.S. total) in 2009. This 440% increase far exceeded the increase in all energy use in the U.S. (45% in the same time frame) and in the transportation sector (75%). Energy use for driving for shopping increased more sharply (160%) than all driving (45%), and energy use for retail freight increased faster (580%) than freight as a whole (120%) (Energy Information Administration, n.d.). Key contributors to the 440% increase are summarized in Tables 1, 3, and 4.

TABLE 3.8: TABLE 3: CHANGES IN FIVE FACTORS RELATED TO INCREASE IN ENERGY USE IN DRIVING TO SHOP SINCE 1969, INDEXED TO 1990 = 1.

Factor use	Factor	1969	1977	1983	1990	1995	2001	2009	2009/1969
Eq. 1	US Population	0.81	0.88	0.94	1.00	1.07	1.14	1.24	1.53
	Households/Person	0.81	0.90	0.95	1.00	0.97	0.99	0.99	1.22
	Person Trips/Household	0.67	0.85	0.94	1.00	1.23	1.12	0.97	1.43
	Vehicle Trips/Person Trip	0.92	0.92	0.92	1.00	0.94	0.95	0.99	1.08
	Vehicle Kms per Trip	0.85	0.98	1.04	1.00	1.11	1.32	1.21	1.41
	VKT for shopping	0.35	0.61	0.79	1.00	1.33	1.60	1.41	4.06
Eq. 2	VKT for shopping	0.35	0.61	0.79	1.00	1.33	1.60	1.41	4.06
	Gallons per km	1.45	1.40	1.16	1.00	0.96	0.93	0.92	0.64
	Driving for shopping	0.50	0.85	0.92	1.00	1.29	1.49	1.30	2.59
	Driving for Shopping Energy Use, EJ	**0.7**	**1.3**	**1.4**	**1.5**	**1.9**	**2.2**	**1.9**	

A low value before 1990 means that this factor increased between that year and 1990. For example, the index value of person trips per household in 1969 is 0.67. This means that if all factors in Equation 1 had been held constant to 1990 values except person trips per household, then VKT for shopping would have increased 33% (1.00 - 0.67) between 1969 and 1990. If all values except vehicle km per trip had been held constant, VKT would have increased only 15% (1.00 - 0.85). Thus, person trips per household had a larger effect on changes in VKT than km per trip. After 1990, the opposite is true: if only vehicle km/trip had changed, VKT would have increased 21% (1.21 – 1.00). Even though fuel economy improved 64% between 1969 and 2009, it was not enough to offset increases in other factors.

TABLE 3.9: CHANGES IN FACTORS CONTRIBUTING TO RETAIL FREIGHT ENERGY USE, INDEXED TO 1987 = 1.

Factor use	Factor / Year	1967	1972	1977	1982	1987	1992	1997	2002	2007	1967 / 2007
Eq. 3	KM/trip	*Data not available; must be inferred from comparing tonnes and VTKT.*									
	Tonnes	0.18	0.38	0.59	0.79	1.00	1.21	1.16	1.13	1.28	7.2
	VTKT	0.42	0.57	0.71	0.86	1.00	1.14	1.36	1.48	1.67	3.9
Eq. 4	VTKT	0.42	0.57	0.71	0.86	1.00	1.14	1.36	1.48	1.67	3.9
	Joules / tkm	0.86	0.97	1.05	1.00	1.00	1.04	1.05	1.06	1.10	1.3
	Retail Freight	0.36	0.55	0.75	0.85	1.00	1.19	1.43	1.57	1.85	5.1
	Retail Freight Energy Use (EJ)	**0.7**	**1.2**	**1.7**	**2.4**	**2.7**	**3.0**	**3.5**	**3.6**	**4.6**	

See the caption for Table 3 for interpretation. The table shows that increase in tonnage was the main driver of change before 1987. After 1987, the sharp increase in tonne-kilometers travelled compared to tonnes (1.67 compared to 1.28) indicates an increase in distance travelled per tonne. Energy per t-km increased relatively steadily between 1967 and 2009, but its contribution to increased energy use in retail freight was much less than the increase in vehicle tonne-km travelled (1.3 compared to 3.9).

Finally, as shown in Table 5 (which uses an LMDI decomposition instead of a Kaya to reduce residuals, see Methods section for details) retail freight accounted for 70% of the increase in total RGM energy use.

TABLE 3.10: LMDI DECOMPOSITION OF RGM ENERGY LOOKING AT ONLY DRIVING-FOR-SHOPPING AND FREIGHT, 1990 = 1.

Effect	1969	1979	1989	1999	2009	Effect for 1969 = 1
D(driving)	0.71	0.94	0.99	1.11	1.10	1.52
D(freight)	0.41	0.72	0.95	1.13	1.37	3.53
Relative change in total RGM energy	**0.29**	**0.68**	**0.94**	**1.25**	**1.51**	**5.39**

Freight drove more of the total RGM energy use change between 1969 and 1990 (1-0.41 = 0.59 which is greater than 1-0.71 = 0.29).

In addition to finding an increase in absolute energy, we found that RGM energy intensity increased per shopping trip (60%), per constant dollar GDP (60%), per retail dollar spent (140%), and per capita (180%).

3D.2: EXPLANATION OF RESULTS

For each of the drivers named in Table 1, excluding increase in population which is outside the purview of transportation policy, we performed further research, both within and beyond the previously-discussed data sets to determine the context of the change. This discussion is summarized in Table 1.

PROPOSED EXPLANATIONS FOR THE INCREASE IN FREQUENCY OF SHOPPING TRIPS 1969-1995

We find four potential explanations for this trend: increase in consumer expenditures, expansion in the utility of shopping, fragmentation of household management, and preference for fresh foods. Average annual shopping trips went from 134 per person (425 per household) in 1969 to 295 per person (725 per household) in 1995.

The increase in shopping trips resulted in part from an overall increase in sheer consumption: Americans in 1969 spent $4550 per capita on goods compared to $6840 per capita in 1990 measured in 2007$ (US Department of Commerce, n.d., fig. 2.3.5). But the increase in frequency of shopping trips outpaced increases in consumer spending: American consumers purchased $64 per trip in 2007$ in 1969 compared to $35/trip in 1995 (~65% less per km driven to shop).

Trips tagged as shopping in the statistics may have shifted in their underlying purpose: since the late 1960s , many scholars have remarked that utility of shopping expanded from merely acquiring goods to include social, romantic, relaxation, and even exercise functions (Havlena & Holbrook, 1986), (Tauber, 1972), (Babin, Darden, & Griffin, 1994).

In addition, in these decades American family life became more hectic, in part due to an increase of women in the workplace, rising from 41% of women in 1970 to 59% in 1995 (Bureau of Labor Statistics, 2011). This, as remarked upon in relevant contemporary literature, fragmented housekeeping efficiency and increased the number of individuals tending to tasks like shopping (*28*) (Gershuny & Robinson, 1988). While time of day for shopping did not shift during our time frame, shopping did shift across days of the week with Sunday' share going from 7.7% to 12.2%. Some scholars have attributed Sunday shopping to women working (Varble, 1976). Gershuny and Robinson's in-depth re-analysis of time-use survey data from 1965-1985 shows that women's domestic work time did decrease significantly, but time for shopping went up slightly both for women and men (Gershuny & Robinson, 1988). Taken together, these factors indicate that shopping activity became more fragmented.

Finally, the goods themselves might have driven change in frequency: Food is the single largest component in retail freight, with 44% of VTKT in 2007. Americans' preference for fresh foods with a shorter home shelf-life rose between 1969 and 2009 (Ukrop, 2010). As an example, per capita consumption of fresh fruits rose 27% in this time, whereas canned and processed fruit rose only by 2%.

EXPLANATION FOR INCREASE DISTANCE PER SHOPPING TRIP, 1983-2009

We find two potential explanations: retail consolidation and exurban commercial sprawl. The retail industry consolidated, going from about nine stores per thousand residents in 1970 to less than four per thousand residents in 2009 (US Census Bureau, 2011). This phenomenon is known as the "Retail Revolution," first named in the economic literature in 1981 (Bluestone, 1981). It began with the rise of the department store and concluded with the widespread presence of Big Box retail and suburban malls. Automobiles with cheap fuel and easy access to roads were complicit; they reduced the consumer's cost of reaching a distant store. Thus, competition among stores increased, driving down margins and favoring stores with more customers (Neumann, 2006). Fewer stores per capita meant that shoppers were less likely to be near a store containing the goods they want. Furthermore, urban sprawl increased distances between retail and residential districts (Burchell et al., 2002). The household surveys indicate that the increase was driven by an increased share of total trips over 21 miles, while trips less than six miles lost share.

EXPLANATIONS FOR INCREASE IN RETAIL FREIGHT TONNAGE, 1967-1987

Retail freight tonnage increased 82% between 1967 and 1987. We find one driving explanation: an increase in sheer consumption by Americans. Americans consumed $4100 per capita 1967 and $6400 in 1987, over a 55% increase. Combined with population rise, this led to increase in total expenditures of 89% (US Department of Commerce, n.d.).

An increase in the dollar density of goods (more tonnes per dollar) would also explain an increase of tonnage. However, the commodity surveys indicate that in 1993, retail goods weighed $1.70/kg (in 2007 dollars) and $2.86/kg in 2007 showing that retail goods in fact have been getting *less* dense per dollar. This gives further culpability to the increase in total shopping expenditures on RGM energy use. Note: The overall freight sector got *more* dense, going from $1.02/kg in 1993 to $0.91 in 2007.

EXPLANATIONS FOR INCREASE IN RETAIL FREIGHT AVERAGE TRIP LENGTH, 1987-2007

We find two drivers for the increase in retail freight average trip length: deregulation of the trucking sector and increase in imported retail goods.

Deregulation decreased truckload (TL) prices (77%) and less than truckload (LTL) prices (between 12% and 35%) per tonne-km despite a large increase in diesel prices (Federal Trade Commission, 2007) (Winston, 1998). This incentivized goods movers to ship more on trucks than trains and barges and to ship longer distances on trucks (Federal Trade Commission, 2007).

While we do not include the distance shipped from foreign countries to the U.S. border in our statistics, we hypothesize that the increase in percent of imported retail goods could have driven up domestic shipping distances. Imports as a percent US GDP have risen from 11% in 1987 to 17% in 2009 (World Bank, n.d.). Imported goods arrive in the U.S. at ports, which may be further from their final destination than were domestic production facilities of earlier decades. For example, 40% of these goods imported to the Ports of Los Angeles and Long Beach are shipped east of the Rocky Mountains (CalChamber, 2011). No previous literature has explored this idea methodically, and it remains a topic for future research.

Some literature has argued that the rise of Just-in-Time (JIT) delivery decreased efficiency of freight, by reducing average payload through prioritization of timing over truck utilization thereby driving up total trip mileage (Whitelegg, 1997). However, McKinnon also pointed out that for the UK (which is much smaller than the US, making results not exactly comparable) there was not overwhelming evidence that this reduction in efficiency due to JIT had, in fact, occurred (McKinnon, 1998) and he and others have also noted that increased centralization from JIT can offset the inefficiencies from potentially lower utilization factors (McKinnon & Woodburn, 1994) (Kohn & Brodin, 2008).

INCREASE IN RETAIL FREIGHT ENERGY INTENSITY PER TONNE-KM

Retail freight energy intensity increased 30% between 1967 and 2007. Yet, each individual mode of freight improved its average fuel efficiency in this time (S. C. Davis et al., 2011). Therefore, the increase in energy intensity must be result of a modal shift from rail and barge (efficient modes) to trucks (inefficient mode). Indeed, trucks' share as a percent of retail goods tkm went from 28% in 1967 to 52% in 2007. Energy intensity for retail freight went up less sharply (30%) than energy intensity for all freight (over 300%) (Schipper et al., 2011). This indicates that the bulk and industrial freight sectors experienced a much stronger modal shift than retail freight.

3E: POLICY IMPLICATIONS

More efficient vehicle platforms, cleaner fuels, slowing/reversing population growth, proper pricing for land use and transportation energy use (as well as our own time), and mass transit for goods and people could let us keep most of the benefits of mobility and trade, without all the detriments. However, because they are not unique to RGM, we do not emphasize them. Our top unique RGM policy conclusions follow, all based on the assumption that the explanations for the trends (as well as the trends themselves) discussed in the preceding paper are accurate:

1. **The same trends affect both driving-for-shopping and retail freight, especially trends related to retail stores, urban planning, and e-commerce. However, saving energy on one side of RGM may cost energy on the other (see Figure 1). Thus, policy that considers these two transportation sub-sectors as one integrated RGM sector may be able to achieve more energy, time, and greenhouse gas savings than policy that considers them apart.**

For example, as mentioned above, the retail industry has consolidated notably in the last four decades, from about nine stores per thousand residents to less than four. On the driving-for-shopping side, this consolidation can and has raised energy use. On the freight side, however, fewer and larger stores mean larger trucks can make deliveries with fewer trips, improving efficiency per tonne-km. Thus, policy that seeks to support smaller local stores needs to consider the both driving-to-shop and freighting implications of store location, clustering of different types of stores, warehousing logistics, and size. Sponsoring consolidated warehousing and delivery for local retailers, for example, may facilitate energy use reduction (and less traffic) on both sides of RGM.

Another prominent example is on-line shopping and delivery, which can eliminate much of the energy use associated with RGM, under the right circumstances (conditions like no missed delivery, low returns, full shopping trip displacement, and no additive air freight). Good policy can facilitate some of these circumstances. For example, policy can help reduced the "missed deliveries" by encouraging business to allow employees to get personal packages at work, and by developing secure standard mailboxes designed for parcels. In addition, state and federal policy makers can work with major delivery-based retailers to reduce the use of aviation for delivered goods via pricing, customer notification and education, and smart predictive logistics and warehousing (see Zappo's practices for an example (Heinemann & Schwarzl, 2010)).

Increased delivery means increased reliance on smaller, parcel delivery trucks for last-mile coverage. These trucks are more amenable to electrification/hybridization than larger freight vehicles.

2. **Policy to encourage transit for shopping needs to take shopping-specific considerations into account.**

People are less likely to use transit for shopping than any other purpose. This is understandable: carrying 20 pounds of groceries on the bus is not particularly pleasant. Examples of shopping transit policy include working with stores to provide same-day home delivery of goods selected in-store, and designing transit vehicles and routes to facilitate shopping. Such programs should be deployed comprehensively with education and incentives for shoppers to achieve real emission reductions: a shopping bus with extremely low ridership will have more emissions per trip than individual cars.

The strong trend of increased shopping trips per week and decreased expenditures per trip offers some hope in this regard: if shopper preference move towards a model of very few purchases per trip, transit or walk/biking could become a more viable option.

3. **Slowing and reversing the modal shift towards trucks (from rail and water) is a critical policy agenda item for freight overall. However, such a shift will not greatly impact retail freight energy use. Thus, policy for retail freight energy reduction must go beyond modal shift.**

Retail freight has experienced much less modal shift to trucks from more efficient modes in the past 40 years compared to freight overall. Because retail freight includes taking goods to the store, it is much less conducive to being taken over by train/barge, and it has always had a much higher modal share for trucks than all freight. Policy oriented at truck-to-rail shift should disaggregate its efforts to focus on commodities conducive to this change.

4. **Changes in the way transportation data is collected can make it more conducive to the RGM framework, as well as other commodity-specific transportation energy analyses and policy.**

The set of unique policies aimed at reducing the energy impact of RGM is a form of commodity-specific policy for reducing transportation energy, which, several researchers have noted, is more effective then generic transportation policy (F. M. Vanek & Morlok, 2000). Better collection of data can facilitate such policy for RGM and other commodities. In the household surveys, more differentiation in the household survey as to the type of shopping trip (window, food, social shopping), better tracking of trip chains, and better compensation for failures in driver recall is needed (Turrentine & Kurani, 2007). Such data can be collected using mobile computing with GPS, and some states and countries are exploring such approaches (Schewel & Kammen, 2010), (Department of Transportation, n.d.), (McGowen & McNally, 2007), (Stopher, Clifford, Zhang, & Fitzgerald, 2008). For freight, more detailed record keeping of shipped goods (such as origin and destination type by warehouse, production facility, retail outlet) is necessary.

5. **The trends that have led to the increase of energy use in RGM (some of which, such as women in the workforce and fresh food, have had positive societal impact) do not derive**

from energy-related factors, such as energy price, energy conservation, or concern for the environmental impacts of fossil energy use. Therefore, the most effective policies to reverse these trends may not be explicitly driven by energy or climate agencies, but may instead relate to safety, quality of life (and quality of shopping experience), or local economic strength.

For example, policy to support more small, local grocery stores may be more successful if presented in a framework of increasing residential property values nearby (Handy & Clifton, 2001), or in the context of reducing obesity in poorer communities (Clifton, 2004). The transportation energy benefits, including RGM would be a happy side effect and perhaps would be more sustainable and scalable due to their association with more politically, financially and emotionally powerful causes.

Many of our policy suggestions reside in the sphere of local and even neighborhood or office policy (mailbox design, deliveries to work), and go outside the boundaries of transportation departments. Transportation energy research and policy must expand its scope if the U.S. is to achieve significant energy use reduction goals, and RGM is one example for a good target of such an expansion.

CHAPTER 3: ACKNOWLEDGEMENTS

The authors thank the Berkeley Fellowship for Graduate Research, the National Science Foundation, and EMBARQ at World Resources Institute for their financial support. The authors also thank Nate Aden, Erica Newman, Jalel Sager, and Imran Sheikh for their comments. Ms. Schewel is deeply grateful to Professors Michael O'Hare, Gene Rochlin, and Dan Kammen at UC Berkeley for their support and guidance on this work after Dr. Schipper lost his battle with cancer during the final months of editing. Dr. Schipper is deeply missed.

4: FOSSIL FREIGHT: HOW MUCH FOSSIL FUEL DOES IT TAKE TO MOVE FOSSIL FUEL?

CHAPTER 4: PREFACE

In the following chapter, Professor Lee Schipper and I use traditional data techniques to measure one facet of the interaction of personal and freight miles travelled (called "i_1" in Equation 1 of Chapter 1, describing the data-driven framework for transportation impact): the transportation of fuel used to support transportation itself (mainly petroleum) as well as other consumption activities. This work is published verbatim under the same title in Transportation Research Record (Schewel & Schipper, 2011) with minor edits to adapt the formatting to match other chapters. Due to Dr. Schipper's sad and untimely passing, I cannot reproduce it here with his explicit consent. However, the committee and I are certain he would have gladly given such consent.

CHAPTER 4: ABSTRACT

This paper asks as the question: how much fossil fuel does it take to move fossil fuel inside the U.S.? An understanding of this "fossil freight", which takes up a significant portion of U.S. freight's capacity, can support new policies or business innovations to halt and reverse the trend of rising energy use in the freight sector. In addition, it can support a more comprehensive view of the impact of fossil fuel use on the environment and economy. In 1970, freight contributed ~4% of U.S. CO_2-eq emissions; by 2007, that figure had risen to nearly 8% (Schipper, Saenger, & Sudardshan, 2011). Furthermore, the carbon intensity of freight movement, as measured in CO_2-eq per ton-mile is still rising, whereas the intensity of passenger travel per person-mile is falling. For freight, this can be largely attributed to a shift in modes: moving to more truck and air freight from rail and barge freight. Previous findings point out the importance of more investigation into the drivers behind the increasing freight emissions, and intensity. This paper tackles one major category of goods that utilize all freight modes, (including pipelines, which are often left out of freight calculations and policy): fossil fuels. The fuel used to move other fuels is called "fossil freight." In 2007, one fifth of freight's energy use went towards the transport of oil, coal, and natural gas products (down from 30% in 1970). Fossil freight absolute energy has remained relatively constant in the U.S. since 1970, due to a variety of balancing forces: whereas fossil fuel use has more than doubled, average trip length for oil and the energy intensity of key modes (such as oil pipelines) has decreased. The decrease in oil trip length, a key driver, coincides with the increase of oil imports, indicating the importance of consideration of the impact that fuel destined for the U.S. has before it reaches U.S. borders.

Fossil freight was responsible for 100% of pipeline tonne-km, 40% of freight rail tonne-km, and 15% of domestic waterborne tonne-km in 2007. These modes are an order of magnitude (or more) less energy intensive than trucking, and several orders more efficient than air freight. As the nation reduces fossil fuel use and frees up this efficient freight infrastructure, leaders must construct policies and plan infrastructure to utilize this capacity for non-fossil freight, and, in doing so, tackle the ever-increasing intensity and greenhouse gas emissions from the freight industry.

4A: INTRODUCTION: EVOLUTION OF CARBON EMISSIONS FROM THE FREIGHT SECTOR

This paper asks as the question: how much fossil fuel does it take to move fossil fuel inside the U.S.? An understanding of this "fossil freight", which takes up a significant portion of U.S. freight's capacity, can support new policies or business innovations to halt and reverse the trend of rising energy use in the freight sector. In addition, understanding fossil freight can lead to a better understanding of the full cost of fossil fuel reliance, and help create the foundation for models to analyze how a move away from fossil fuels would affect U.S. freight industry.

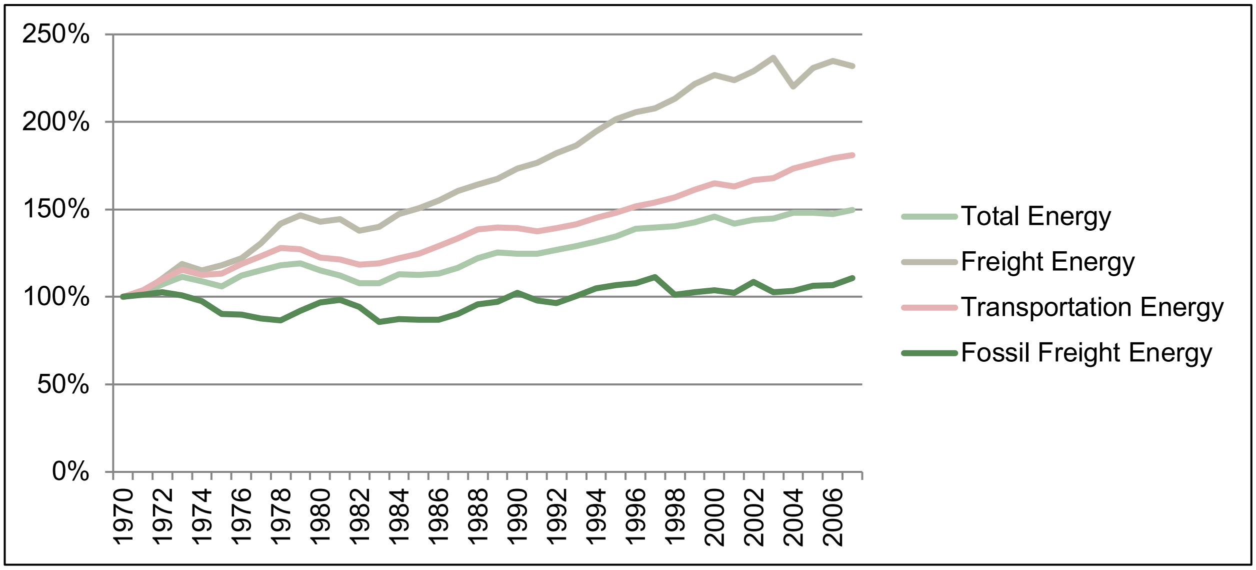
Transportation in the U.S. accounted nearly 2000 million metric tonnes (CO_2 equivalent) of greenhouse gas emissions in 2007 (Energy Information Administration & Department of Energy, 2009), and the rate of increase in emissions from transportation emissions is rising faster than the rate of total emissions. While much attention from the policy and academic communities have been directed towards consideration of how to reduce this figure, the majority of these discussions have focused on the movement of people (Ross Morrow, Gallagher, Collantes, & Lee, 2010). However, as pointed out in Schipper (Schipper et al., 2011), freight has come to play an increasingly large role in U.S. transportation emissions and energy use (see Figure 1). The US is not alone in this phenomenon: interest in Europe and other OECD countries is also turning towards the rising impact of freight ((Tapio, Banister, Luukkanen, Vehmas, & Willamo, 2007), (Kamakaté & Schipper, 2009)). In 1970, freight contributed ~4% of U.S. CO_2-eq emissions; by 2007, that figure had risen to nearly 8%. Furthermore, the carbon intensity of freight movement, as measured in CO_2-eq per ton-mile is still rising, whereas the intensity of passenger travel per person-mile is falling. For freight, this can be largely attributed to a shift in modes: moving to more truck and air freight from rail and barge freight. Often, oil and natural gas pipelines are left out of freight calculations (such as in the 2010 paper cited above), and adding them will exacerbate calculation of rising impact of freight (Schipper et al., 2011).

These previous findings point out the importance of more investigation into the drivers behind the increasing freight emissions, and intensity. This paper tackles one major category of freighted goods: fossil fuels. In this paper, the transportation of fossil fuels is called "fossil freight." In 2007, one quarter of freight's energy use went towards the transport of oil, coal, and natural gas products. These figures exclude the losses incurred "freighting" of electrons over transmission and distribution wires, which accounted for 6.5% of generated electricity in 2007 and substituted in part for bulky fossil fuels that provided space and water heating, as well as process energy and traction now supplied by electricity to rail and trolley systems (Energy Information Administration, 2009). About 70% of electricity was generated in 2007 from fossil fuels; therefore, the losses incurred in transmission and distribution of fossil-generated electrons was 700 billion mega joules (Energy Information Administration, 2010).

This share of fossil freight energy is so large that changes in fossil fuel use patterns could have a significant impact on total freight haulage and the industry's structure. If fossil fuels were replaced by biofuels, the share of energy in freight could remain high, especially if it exacerbated the current freight modal shift to trucks. If more of the present use of fossil fuel was replaced by electricity, with its inherent losses in transmission, different changes in the "freight bill" would emerge. If lower carbon emissions were ushered in primarily by lower-than-otherwise fuel use (efficiency), then the national freight haulage and its fuel use would be lower than otherwise.

FIGURE 4.3: INDEX OF ENERGY USE IN US, TRANSPORTATION, FREIGHT AND FOSSIL FREIGHT. 1970 = 100%.

While freight energy has increased at a higher rate than total energy and transportation energy as whole, fossil freight energy has remained relatively constant.



As shown in Figure 1, the energy use for fossil freight has remained relatively constant. The results section of this paper will explore the drivers behind this statistic, specifically how tonnage has increased, while mileage has decreased. Figure 2 shows total freight tonne-km, broken into mode (color) and fossil-freight versus non fossil freight (shading). Since 1970, trucking (blue) has come to play a large role in freight, driving up industry energy intensity and greenhouse gas emission. While trucking attributed to fossil fuels remains low relative to other trucking—dominated by the last-mile delivery of gasoline to gas stations--a continuation of this trend could rapidly drive up fossil freight emissions, as trucking is orders of magnitudes more energy and greenhouse gas intensive than some of the other fossil freight modes and therefore has an impact on these impacts compared to its tonne-mileage (see Figures 3 and 4). Fossil freight (almost entirely coal) has been eating up rail capacity compared to non-coal shipments since 1970. While waterborne shipments for all forms of freights has diminished.

FIGURE 4.4: FOSSIL FREIGHT CONTRIBUTION TO ALL FREIGHT TONNE-KM, 1970, 1990, 2007

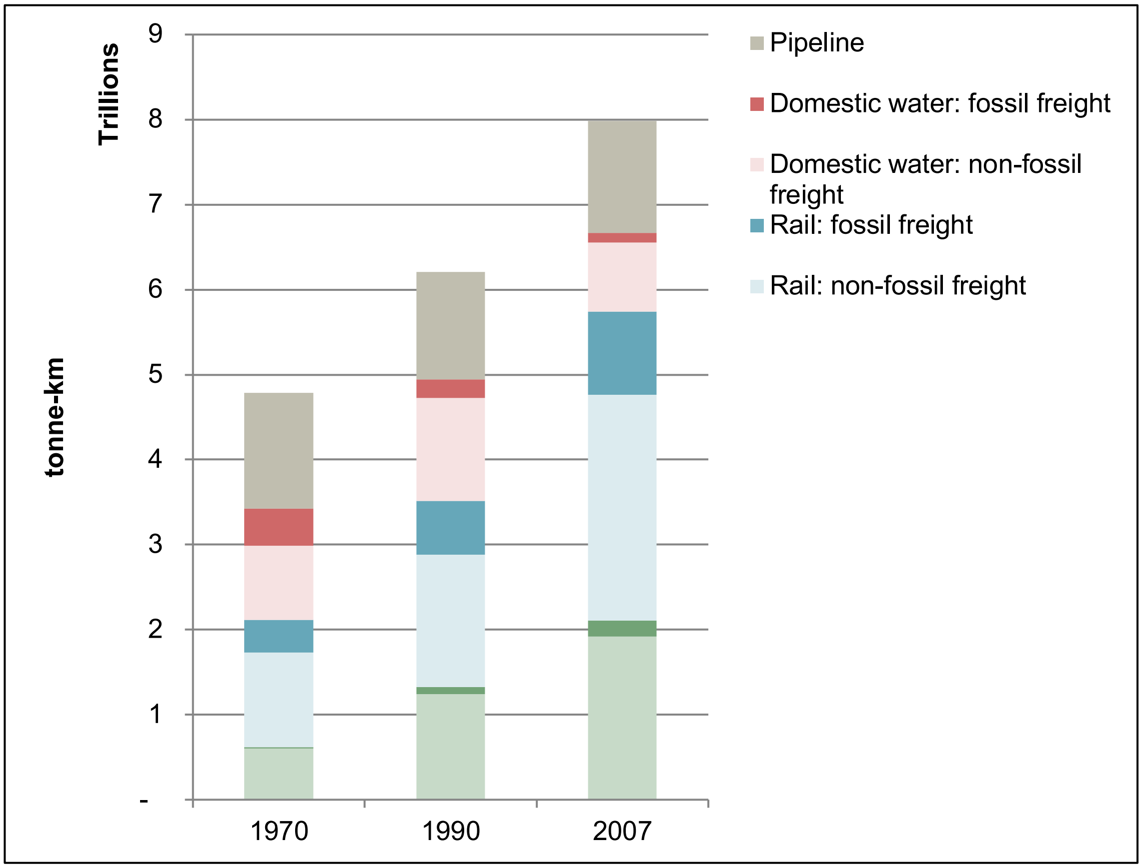


FIGURE 4.5: FOSSIL FREIGHT CONTRIBUTION TO FREIGHT ENERGY, 1970, 1990, 2007

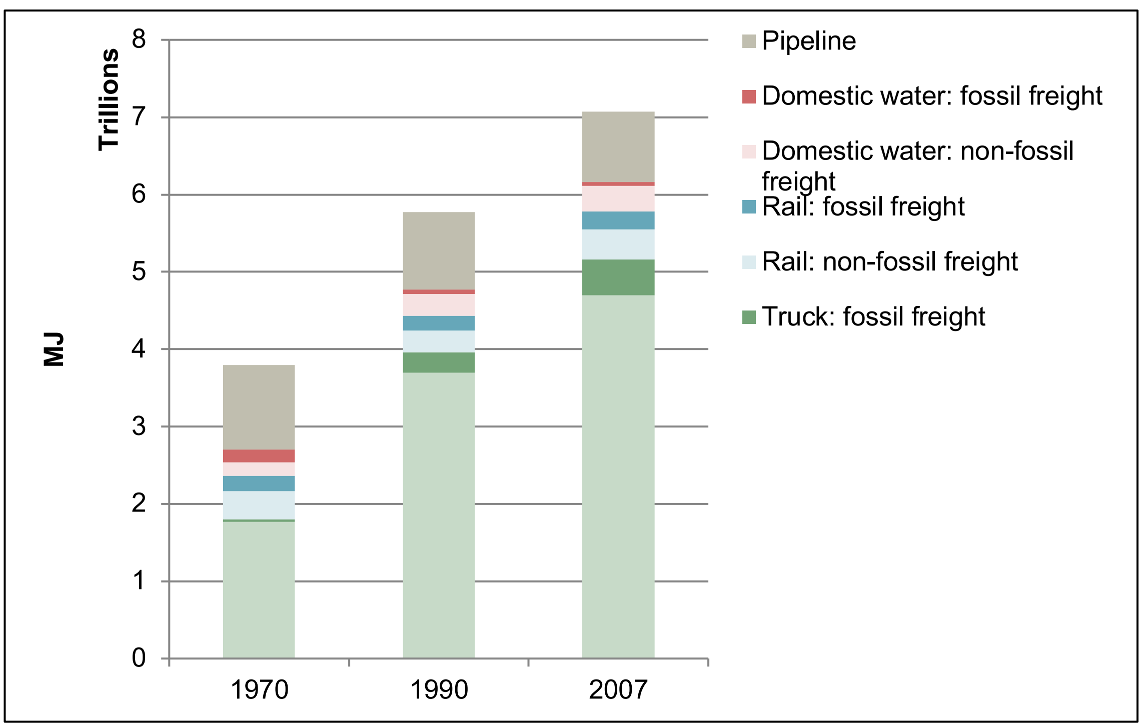
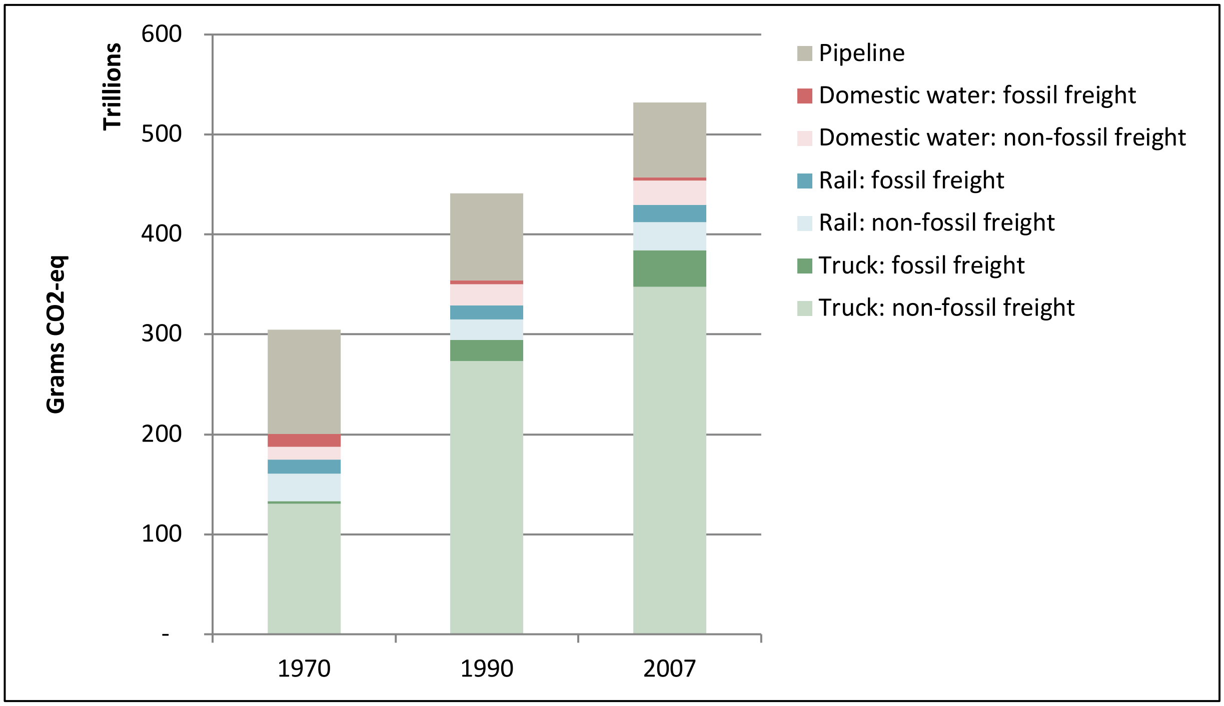


FIGURE 4.6: FOSSIL FREIGHT CONTRIBUTION TO FREIGHT CO2-EQ EMISSIONS FROM FREIGHT BY MODE, 1970, 1990, 2007.

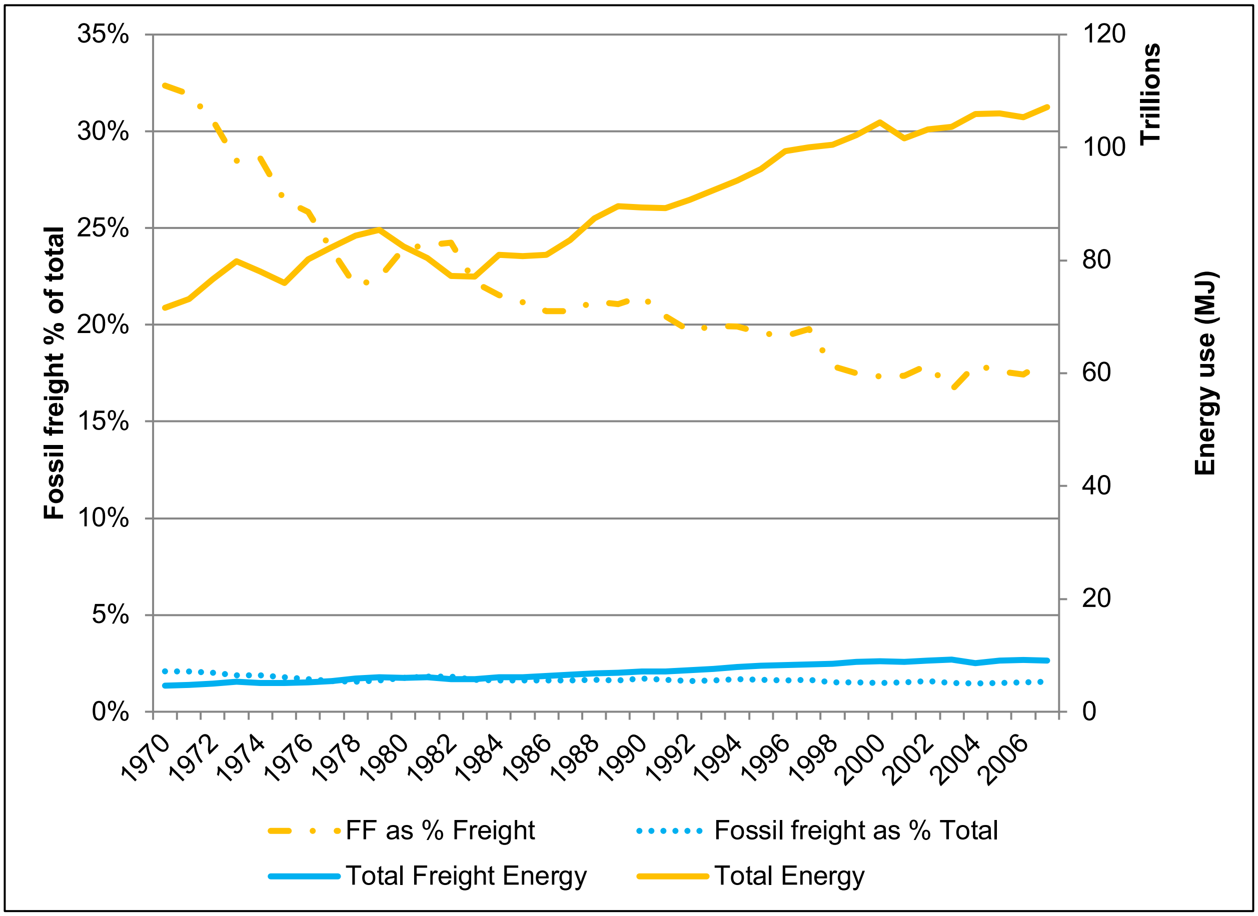


4B: FOSSIL FREIGHT DEFINITION

"Fossil freight" refers to the fuel used to transport fossil fuels. The transportation of fossil fuels contributes over 30% of domestic freight tonne-km. These "upstream" emissions associated with using fossil fuels are usually seen as a small addition to the life cycle assessment of any product that uses fossil fuels, such as a vehicle. This paper attempts to aggregate all energy use and emissions associated with the transportation of fossil fuels within the United States, and to determine any historical drivers behind changes in these emissions. Fossil freight energy has remained relatively constant in the U.S. since 1970, due to a variety of balancing forces: whereas fossil fuel use has more than doubled, average trip length and the energy intensity of key modes (such as oil pipelines) has decrease. Emissions from fossil freight have decreased as a result of the greening of the electrical grid and reduction in leakage from natural gas pipelines in addition to the factors influencing energy.

As shown in Figure 5, total energy use in the U.S. has grown since 1970, as has total freight energy (solid lines, axis on right). The percent of total energy use attributed to fossil freight has decreased slightly, and the percent of fossil freight as a contributor towards total freight has decreased significantly (dotted lines, axis on left). This, as indicated in Figure 3, can be attributed to the rise of trucking in non-fossil freight since 1970.

FIGURE 4.7: TOTAL U.S. ENERGY USE (ORANGE, SOLID) AND FREIGHT ENERGY USE (BLUE, SOLID) AS WELL AS DOMESTIC FOSSIL FREIGHT AS A PERCENT OF EACH FROM 1970-2007 (DOTTED).



Fossil freight's percent of freight energy has decreased as non-fossil freight moved to energy-intensive trucking mode. Fossil freight's contribution as a percent of total energy has remained relatively constant between 1.5 and 2.5%.Note: fossil freight only includes movement within the U.S.; much fossil freight energy use is "exported" in the movement of fossil fuels through, for example, Canadian pipelines and overseas oil tankers.

4C: APPROACH

Fossil fuels include petroleum, natural gas, and coal. The approach taken here is bottom up: the researchers scanned data going back to 1970 (where available) to find indicators of fossil fuel use and transportation to build the data set of energy use, tonne-miles, and tonnes for each fossil fuel. For each fuel the procedures were somewhat different, as outline below:

Oil: For ton-miles of oil pipeline freight back to 1980, the Bureau of Transportation Statistics' Improved Ton-Miles Estimates were used (Bureau of Transportation Statistics, 2010). For ton-mile movements prior to 1980, the 1980 data point was scaled relative to total oil and usage. For all oil movements and tonnage not in pipelines, the Department of Transportation's Commodity Flow Survey (CFS) and its predecessors were used. These data were collected only every five years (and not during 1987 or 1982) (US Department of Transportation, Bureau of Transportation Statistics & US Department of Commerce, US Census Bureau, 2006). Linear growth was assumed between each data point available from the CFS. The value for energy intensity of oil pipelines through 1982 was taken from a 1982 study by the Congressional Budget Office (0.36 MJ/tonne-km) (Congressional Budget Office Staff, 1982), and after 1982 a value was used from the Trans-Alaska Pipeline Survey Environmental Impact Report (0.22 MJ/tonne-km) (Argonne National Lab, n.d.). Energy intensity for other modes was taken from the Transportation Energy Data Book, henceforth TEDB (Davis, Diegel, & Boundy, 2009) and the National Transport Statistics (Bureau of Transportation Statistics, 2010). The share of light trucks not used as personal vehicles, as well as proportional shares of light truck VKT and fuel us were taken from the TEDB, based in turn on TIUS and VIUS (Schipper et al., 2011). Light trucks were assumed to carry 200 kg of freight, and medium trucks (single body) three metric tonnes to add their freight haulage to that of interstate trucking noted in TEDB. Tonnage of oil in pipelines was taken from the Bureau of Transportation Statistics, and only reported every 10 years between 1960 and 1990 (and not at all after 2001) (McKinnon, 2007). For missing data points, the tonnage was estimated to grow linearly between known data points. For dates after 2001, tonnage was assumed to grow at the same rate as ton-miles. Distance data was not explicitly available for any mode for oil; however, average trip distance by mode could be ascertained by dividing ton-mile data by tonnage.

Natural gas: All natural gas movement was assumed to occur in pipelines; most CFS data sets combine liquefied natural gas (LNG) moved in trucks with "other petroleum products," and LNG tonnage is very small compared to total petroleum movements, and so these movements were bundled with the oil movements (The BTS estimated total ton-miles for natural in pipelines from 1980 (Bureau of Transportation Statistics, 2010). This estimate was made by taking the total tonnage of natural gas in pipelines, and applying the average trip length of oil in oil pipelines, a method which, as we explain below, may have underestimated the total ton-miles. The total energy used in pipelines, storage and transmission is available from the Energy Information Administration's Annual Energy Review (AER) (Energy Information Administration, 2010). Therefore, for natural gas this direct energy use figure was used, instead of multiplying energy intensity per tonne-km by tonne-km to get total energy use (as done for oil and coal).

Estimates of energy intensity of natural gas pipelines were available from Argonne National Labs. This figure, around 300 btu/tonne-km, was a factor of four times as small as the btu/tonne-km that would be derived by dividing the EIA's total energy use in pipelines by the BTS' estimate of tonne-km (Wang & Huang, 1999). This indicates that either the tonne-km estimate used by the BTS is low, or that much energy is used in storage inside pipelines.

To calculate the greenhouse gas impact of pipelines, leakages must also be taken into account. This data was taken from the EIA's inventory of greenhouse gases, from the natural gas transmission, storage, and distribution categories (Energy Information Administration & Department of Energy, 2009). Data was only available back to 1990. For dates previous to 1990, the leakages were indexed to the change in total natural gas tonne-miles between 1990 and the target year.

Coal: Coal movements proved challenging to document. The Energy Information Administration (EIA)'s Coal Transportation Rate Database (CTRDB) provides detailed records, including tonnage and distance by mode from 1979 to 2001 (Energy Information Administration, 2004). However, the database only captures a portion of all coal shipments. The EIA's Coal Distribution report compilation covers all shipments of coal by tonnage and mode from 1994 through 2008, but does not give distance. It does, however, give origin and destination states. Therefore, the average distance between each pair of states by mode was calculated from the CTRDB data and these averages were applied to the data included in the CD set to estimate the ton-miles travelled by coal from 1994-2008. For data before 1994, tonnage was taken from the EIA's Annual Energy Review (Energy Information Administration, 2010). The percent of the total shipments ascribed to each mode of travel were matched to the percent of shipments on each mode of transport (by weight) from the CTRDB, and the average trip length for that year per mode was applied to the new estimate of tonnage for each mode. All years before 1970 were fixed to 1979 percentages.

Intensity: Next, the energy intensity, as measured in MJ per tonne-kilometer were estimated. Data for intensity for barges, rail, trucking and air freight were taken from the Transportation Energy Data Book (Davis et al., 2009). A key assumption is that fossil freight haulage occurs largely at the same energy intensities as other freight. This may be inaccurate for two reasons. First, most fuel haulage is by long distance, often unit trains of only coal or oil or dedicated tanker trucks barges or tankers. These would have low energy intensities because of the scale. However, they have to return largely empty, particularly when liquid fuels are hauled, to avoid mixing fuels of differing types. Thus the use of average energy intensities by mode is only a first approximation.

Each mode of transportation was assumed to use one fuel (except for rail before 1979, which used both diesel and coal). All trucks were assumed to use diesel, all domestic shipping was assumed to use bunker fuel, oil pipelines were assumed to use electricity, and natural gas pipelines were assumed to use natural gas. Rail was assumed to use diesel (Energy Information Administration, 2010). Using standard CO_2 coefficients with 100-year global warming potential values, these fuel consumption data for diesel and natural gas combustion are converted into CO_2-eq emissions (including CO_2, N_2O, CH_4, and HFCs, 100 year values) using 2007 emissions factors from the US EPA Inventory of Greenhouse Gas Emissions (Environmental Protection Agency, 2010). Natural gas leakages from pipelines and storage were added to the CO_2-eq emissions count as methane. The electricity used for oil pipelines was converted to CO_2-eq emissions per kWh delivered at US average fuel mix for the year in question, as documented in the the AER (Energy Information Administration, 2010).

Each of these data sets yielded uncertainty, either from the methods used by others to build the set, or by missing pieces that had to be filled in through projection. Because data sets rarely reported spreads or incompleteness, and where they did report, the format and methods differed, overall uncertainty for calculations in this paper were not calculated.

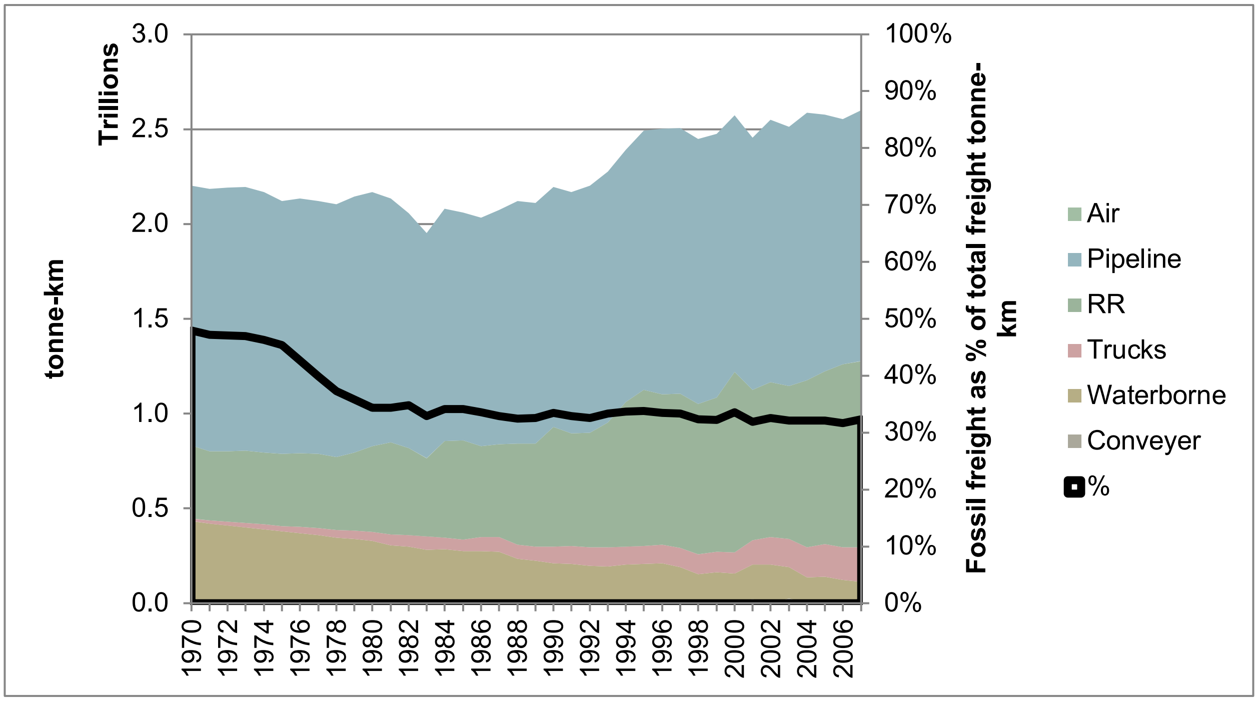
It is also important to note that these estimates include fossil fuel moved only within the country. Therefore, the movement of oil from the field to a refinery in Saudi Arabia, and then from that refinery across the sea to a U.S. port is not captured (the movement of that oil from the port to the end destination is captured). Expanding the data set to include movements outside the U.S. is an important future project to understand the full upstream costs of using fossil fuel.

Next, a simple decomposition analysis was performed. For a discussion of more complex decomposition analyses, please see the author's previous paper (Schipper et al., 2011). This work is carried out in S.I. units.

4D: RESULTS: FOSSIL FREIGHT WAS RESPONSIBLE FOR ~1.5% OF US ENERGY USE AND ~3% OF CO2-EQ EMISSIONS IN 2007

Tonne-km of fossil fuel shipped by mode are shown in Figure 6. The share of fossil freight in total domestic freight (including NG and oil) was 35% in 1980 and 32% in 2007. Note: All data for total fossil freight was taken from BTS NTS. For years 1980 and later, BTS has improved statistics for freight that tend to increase the total tonne-km. Therefore, the decrease in fossil freight as percent of total freight reflects this change in data interpretation.

FIGURE 4.8: FOSSIL FREIGHT TONNE-KM AND AS PERCENT OF TOTAL FREIGHT TONNE-KM, 1970-2007.



Pipelines, often left out of freight discussions, dominate fossil freight tonne-km. Tonnes have increased more than kilometers, as shown in Table 1. The authors hypothesize that this is because of the increase in imported fossil fuels: points of entry—such as ports—are closer to end-users than traditional extraction locations. However, this hypothesis requires more testing.

Fossil freight energy use remained constant since 1970, using 1.7 x 10^{12} MJ of energy in 2007, compared 1.5 x 10^{12} MJ in 1970. As both transportation and total U.S. energy use increased over this time period, fossil freight as a percent share of total energy use went from 2.1% to 1.5%, as a percent total transportation energy use it went from 8% to 5% (assuming transportation energy totals include pipelines).

4D.1: INTERNATIONAL MOVEMENTS OF FOSSIL FREIGHT NOT INCLUDED IN THIS ANALYSIS

These calculations exclude at shipping of imported oil, coal and LNG or CNG to US harbors. In terms of tonne-km this is a serious omission. While full estimates of this figure are not feasible at this time, a few back-of-the-envelope calculations illustrate the magnitude of these additional emissions:

- Canada, the U.S.'s largest oil import partner, sends about nearly 2M bbl/day of its domestic oil production to the U.S. This accounted for about half the total consumed and exported oil in Canada in 2007. If one assumes that therefore, U.S. exports are also responsible for half of the tonne-miles and energy use in oil pipelines in Canada, then an additional 62 billion tonne-km should be added to the U.S. fossil freight bill, increasing oil pipeline tonne-km by 11% (North American Transportation Statistics Database, 2009).

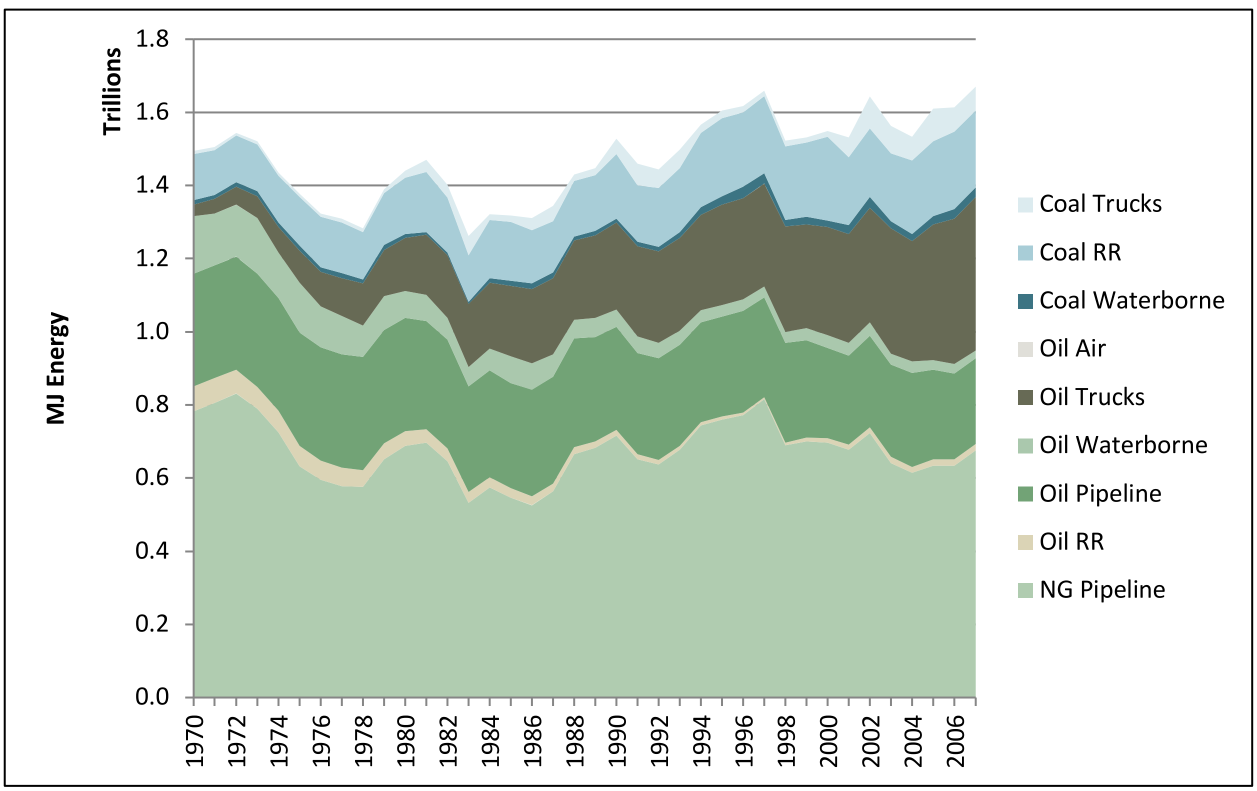
- 12% of international maritime fuel was consumed by transporting crude oil in 2007 (Crist, n.d.). The US consumers one quarter of global oil, and about 40% of U.S. oil comes from countries besides Canada (and thus, are presumed to send oil overseas). Thus, a rough estimate indicates that including maritime fuel for imports could add it would add ~1.7 x10^{11} MJ to the U.S. fossil freight bill, or 10% on top of the total freight energy cited above.

Shipping oil via tanker is far more efficient than any other mode: therefore, it is possible that importing fossil freight in exchange for reduced ton-mileage domestically (in pipelines) may have reduced overall energy use from fossil freight, even though the distances involved are up to an order of magnitude farther. Note too that both dedicated rail cars and tankers return empty.

As shown in Figure 7, natural gas and oil movements in pipelines dominate fossil freight energy consumption, due to high energy intensity and mileage of pipelines and the preponderance of short-haul trucking in the oil sector (most gas stations, for example, are serviced by trucks that pick up gasoline a several miles away at a depot connected to a pipeline).

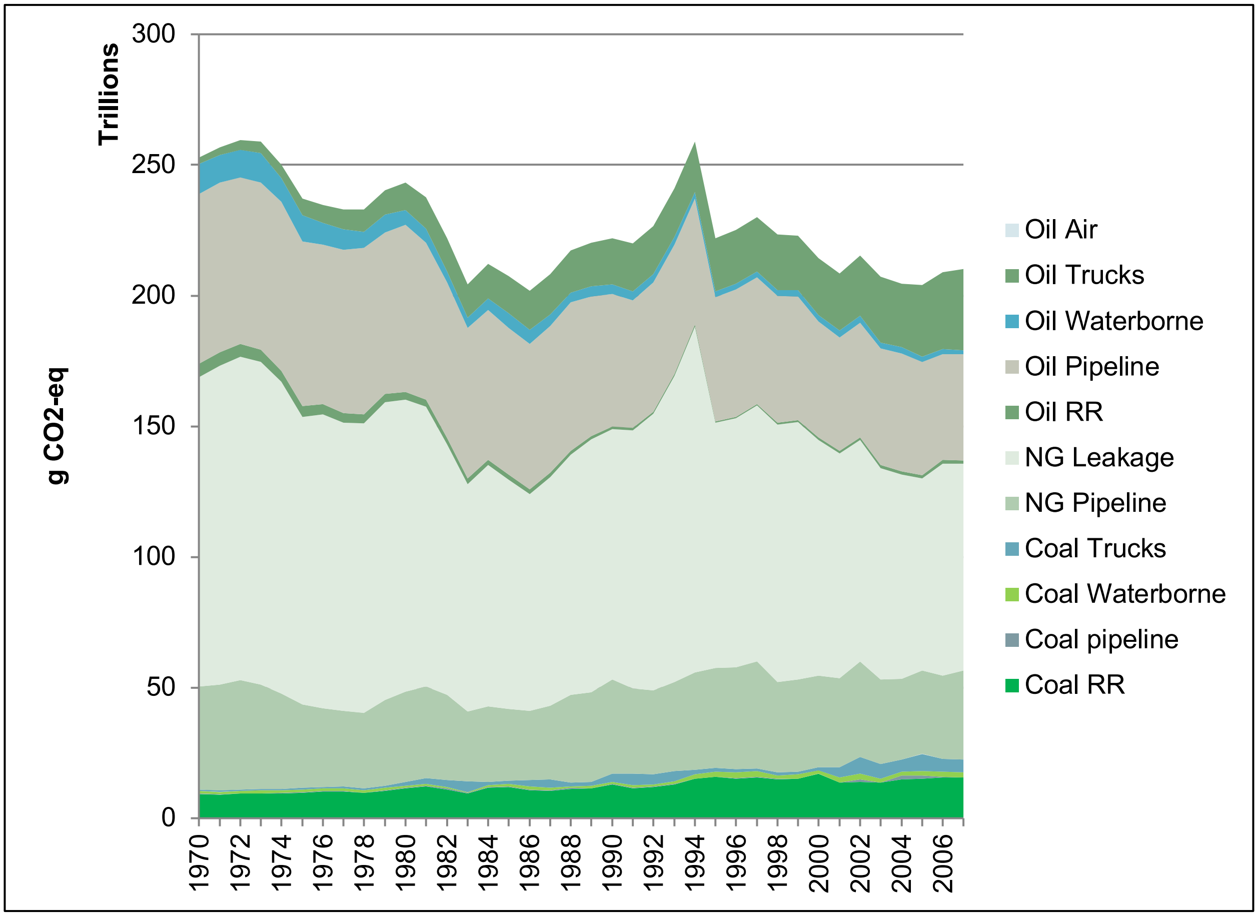
As shown in Figure 1, the amount of energy used in freight has been changing much more slowly than all other transportation categories, as well as total U.S. energy use. The reasons behind this are explored in the Laspeyres analysis section.

FIGURE 4.9: TOTAL FOSSIL FREIGHT ENERGY BY MODE AND FOSSIL FUEL SHIPPED, 1970-2007.



Fossil freight created ~210 MT CO_2-eq emissions in 2007, down from 250 MT CO_2-eq in 1970. This moves from 4% to 3% of all US emissions, including leakage from natural gas pipelines.

FIGURE 4.10: GRAMS CO2-EQ FROM FOSSIL FREIGHT, BY MODE AND FOSSIL FUEL SHIPPED, 1970-2007.



Fossil freight intensity has gone from 0.7 MJ/tonne-km in 1970 to 0.6MJ/tonne-km in 2007. The average intensity for all freight was ~3.8 MJ/tonne-km, over six-fold greater than fossil freight. This is due to fossil freight's low reliance on trucking and aviation, and high reliance on trains and pipelines. However, truck use (or data collected about truck use) has increased ten times over since 1970, a trend that could being to temper fossil freight's efficiency credibility if it continues.

4D.2: WHY AND HOW DID ENERGY USE AND GREENHOUSE GAS EMISSIONS CHANGE? A LASPEYRES ANALYSIS.

The following table shows a Laspeyres index for several potential drivers behind the fossil freight energy tab for the years 1970, 1980, 1990, 2000, and 2007. The table shows that different factors are balancing to create the slight decrease energy use in fossil freight. Between 1970 and 2007, whereas tonnage (a close proxy for total U.S. fossil fuel use) more than doubled, the average trip distance nearly halved, leading to only a slight increase in tonne-km. This decrease is driven largely by a ~75% decrease in reported average domestic trip distance for oil (within US borders, not on sea or Canadian pipeline); coal average trip length remained relatively constant, and natural gas reported average distance dipped in the mid 1980s, then returned to 1970s levels. Then, a reduction in energy intensity per tonne-km compensated for the remaining increase in tonne-km. Energy intensity also went down, balancing an increase in tonne-km.

TABLE 4.11: INDICES OF VARIABLES IN ENERGY USE FOR FOSSIL FREIGHT FOR FIVE SELECTED YEARS. 1990 = 100%.

All Fossil Freight	1970	1980	1990	2000	2007
Energy Use	97%	95%	100%	101%	107%
Intensity (MJ/tonne-km)	97%	96%	100%	85%	91%
Tonne-km	100%	99%	100%	119%	118%
Average Trip Distance	155%	121%	100%	99%	69%
Tonnage	65%	81%	100%	118%	147%

TABLE 4.12: LASPEYRES INDEX OF FOSSIL FREIGHT 1970-1990 WITH 1990 = 100%

	1970	1980	1990	2000	2007	1970-2007
Actual emissions	114%	110%	100%	97%	95%	-19%
Activity (tkm)	100%	99%	100%	117%	118%	18%
Mode shift	98%	101%	100%	95%	99%	1%
Carbon intensity	115%	111%	100%	87%	82%	-33%
Fuel Mix	106%	110%	100%	98%	96%	-10%
Fuel Intensity	124%	103%	100%	87%	83%	-41%

As Table 2 shows, a reduction in carbon intensity of the energy used to move fossil fuel and the intensity of the fuels used are the largest drivers behind the decrease in greenhouse gas emissions from fossil freight. Improvements in the carbon intensity of electricity, reductions in the fuel intensity of trucks, barges, and trains, and reduction in leakages from natural gas pipelines all contribute to these trends.

4D.3: INCLUDING PIPELINES IS IMPORTANT FOR POLICY MAKERS

If included in analyses of freight, pipelines would significantly change the energy and carbon impact of the freight sector. The following table shows the impact of including pipelines in a freight analysis.

TABLE 4.13: KEY INDICES WITHOUT PIPELINE DATA.

	1970	1980	1990	2000	2007
Energy Use	73%	86%	100%	110%	137%
Intensity (MJ/tonne-km)	94%	97%	100%	86%	101%
Tonne-km	89%	84%	100%	128%	136%
Average Trip Distance	113%	100%	100%	126%	56%
Tonnage	50%	74%	100%	123%	171%

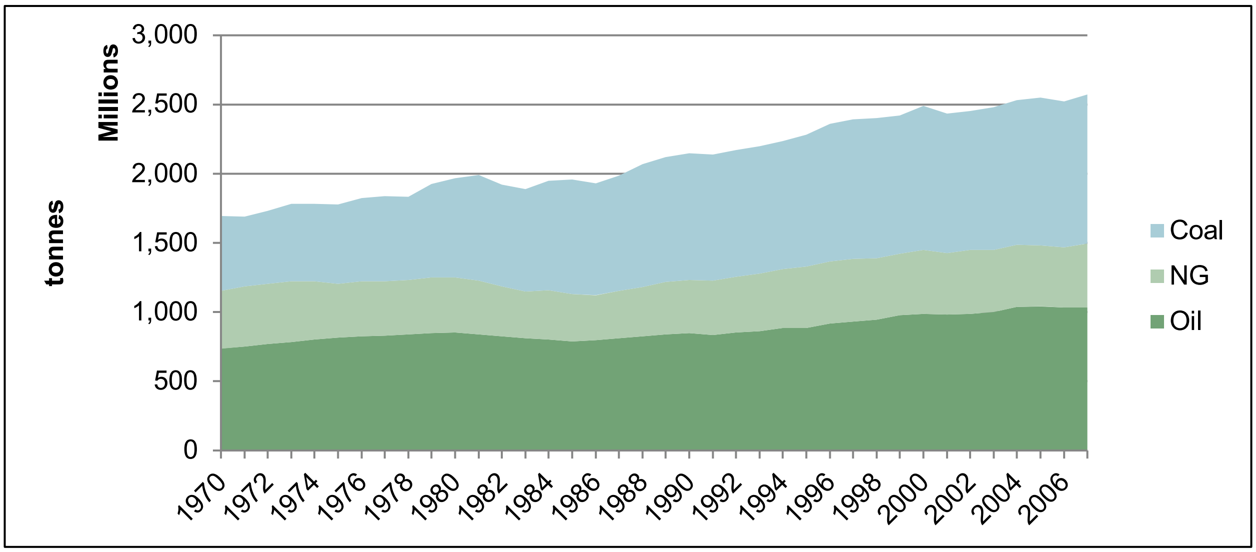
Table 3 implies that exclusion of pipeline data masks the trends noted above: energy use appears to have gone down more rapidly, as does intensity. Tonne-km appear to have gone up less rapidly because the baseline in 1970 (or any year) is larger. Table 3 shows, for each category as well as carbon dioxide equivalent emissions, pipeline-only data as a percent of the sum of non-pipeline data.

TABLE 4.14: PIPELINE CONTRIBUTION AS PERCENT OF NON-PIPELINE SUM FOR EACH KEY CATEGORY.

	1970	1980	1990	2000	2007
Energy use	31%	20%	16%	12%	11%
Tonne-km	53%	37%	31%	28%	24%
Tonne s	125%	91%	73%	66%	49%
CO2-eq emissions	43%	29%	21%	14%	13%

Table 4 indicates that by ignoring the contributions of pipelines, policy makers seeking to understand and address freight could be missing up to half of domestic freight tonnage, under-attributing CO_2-eq emissions as well as energy use and tonne-emissions to the freight sector. Pipelines are shrinking relative to energy use, tonnage, etc for all fossil freight because of the rise of trucking for oil, and increase in coal use.

FIGURE 4.11: TOTAL FOSSIL TONNAGE CONSUMED IN U.S., 1970-2007.

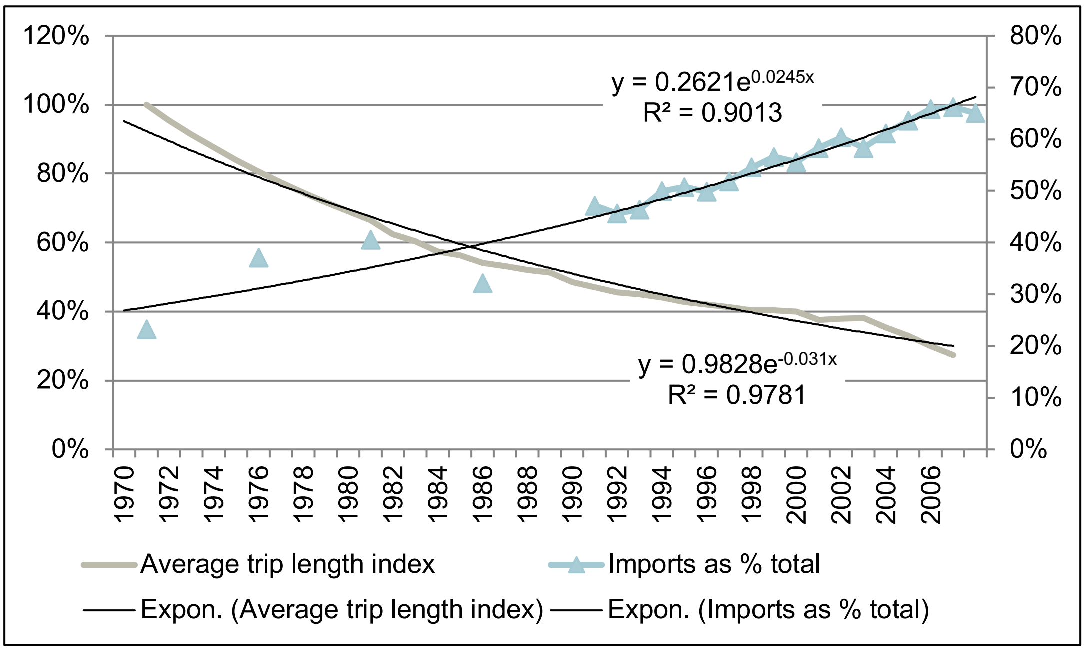


4D.4: TRIP LENGTH

Trip length was calculated in different ways for different fuels, depending on data availability. For coal data, average trip length for each mode was calculated using the CTRDB (see Method section, above). For oil and natural gas, average trip length was taken from diving tonne-km by tonnes shipped.

It is impossible to discern, from these data, why the average trip length for oil decreased so significantly, while trip length for coal remained relatively constant and natural gas length dipped in the mid 1980's and then returned to 1970's levels. One hypothesis is that decreasing average trip length coincides with an increase in oil imports, shown in Figure 10. If the distance between oil intake ports locations and locations where pipelines cross from Canada (the U.S.'s primary import partner) are closer to oil use centers than traditional domestic oil production locations, it could partially or fully account for the decreasing trip length trend. The trend for imports as percent of total consumption and average trip length are almost exactly inversely proportional, indicating that integrating the out-of-country transportation will be an important theme for future research. The importance of capturing out-of-country or "spilled" emissions from manufacture and freight of for all consumed goods has been pointed out recently, and named consumption-based accounting (Schipper et al., 2011). Capturing global fossil freight emissions from fossil fuels used in the U.S. will require significant additional research, and may be hindered by even more challenges relating to historical data availability.

FIGURE 4.12: IMPORTS AS PERCENT OF TOTAL OIL USE IN THE U.S. COMPARED TO AVERAGE TRIP LENGTH FOR OIL INDEXED TO 1970, 1970-2007



4E: CONCLUSIONS AND IMPLICATIONS FOR POLICY AND FUTURE RESEARCH

Fossil freight contributes significantly to U.S. freight haulage, energy use and greenhouse gas emissions. Reducing use in fossil fuel use through improved efficiency will have compound benefits in reducing fossil freight energy and emissions. However, when fossil fuel use reductions are achieved through substitution of other fuels, care must be taken to avoid "hidden" increases in fossil freight energy use and emissions. The average intensity of non-fuel freight per tonne-km is almost four times as high as fossil freight. Therefore, care should be taken to structure any policy pushing towards replacement fuels that require transport (such as biomass and biofuels and an increase in natural gas for electricity production over coal) so as to resemble the fossil freight infrastructure, as opposed to the standard freight infrastructure. Ethanol, for example, is often transported in trucks instead of pipelines, adding to its freight bill (Spatari, Zhang, & MacLean, 2005). In addition, it is critical for researchers and policy makers to include the impacts (transportation and otherwise) emerging from the processing of fuels abroad, before and while they are imported into U.S. boundaries. This will require new approaches to data collection.

Making good on such an attentive policy program requires several additional activities: better availability (digitization in usable format) of historical records, better and more transparent record keeping of major freight and fuel movements going forward, inclusion of pipelines as part of freight, and using figures fully burdened with "up-stream" energy and greenhouse gas costs (including transportation) when calculating the impacts of any new energy policy. Our work reconciles diverse sources of varying quality, particularly before 1980. Our reach far back to 1970, however, permits at least a cursory view of trends just as the first oil crisis occurred and there after

The prospect of a reduction in fossil freight opens up an intriguing long term policy questions. Fossil freight in 2007 was responsible for 100% of pipeline usage, 40% of freight rail tonne-km, and 15% of domestic waterborne tonne-km. These three modes are an order of magnitude (or more) less energy intensive than trucking, and drastically more efficient than air freight. As the nation reduces fossil fuel use and frees up this efficient freight infrastructure, can leaders construct policies and plan infrastructure to utilize this capacity for non-fossil freight, and, in doing so, tackle the ever – increasing intensity and greenhouse gas emissions from the larger freight industry? Will fewer shipments of oil and coal by rail allow faster shipments of other goods by rail rather than truck? Answering such a question requires extensive conversation and integration between engineers, policy makers, and business leaders.

5: SMART TRANSPORTATION: SYNERGIZING ELECTRIFIED VEHICLES AND MOBILE INFORMATION SYSTEMS

CHAPTER 5: PREFACE

In the following chapter, Professor Dan Kammen and lay out how progress in data collection techniques via mobile phones can be used to increase adoption of electric vehicles. In Chapter 6, I put this framework into practice, with additional co-authors, for a specific region. This work is published verbatim in Environment: Science and Policy for Sustainable Development under the same title with minor edits to adapt the formatting to match other chapters (Schewel & Kammen, 2010). I reproduce it here with the consent of my co-authors.

CHAPTER 5: ABSTRACT

For the typical American household, the single most environmentally impactful choice that can be made is to buy a more fuel efficient vehicle (Gardner & Stern, 2008). In 2008, the average American household spent $2715 on gasoline and $1353 on electricity (Bureau of Labor Statistics, n.d.), and the transportation sector was responsible for the same amount of greenhouse gas emissions as the electrical sector (Environmental Protection Agency, 2010). Whereas other household carbon- and energy-saving measures (such as eating less meat, switching light bulbs, or reusing shopping bags) require consumers to remember to and choose to change behavior repeatedly and/or in small ways (which has proved extremely challenging), the vehicle purchase decision happens once every few years. Therefore, policies to influence this consumer decision can have a higher impact on national sustainability, per individual decision, than those that seek to change other consumer decisions.

In the next several years, policy-makers have just such an opportunity with the arrival of the mainstream electrified, or plug-in vehicle coming simultaneously with the explosion of smart-phone enabled mobile information systems. It is technically feasible for a fully electrified vehicle using energy from 100% renewable resources to completely eliminate greenhouse gas emissions associated with personal vehicle fuel use. To ensure consumer acceptance and rapid scale up, however, more must be done, and mobile information systems can play a valuable part. These systems can not only enhance the success of plug-in vehicles, but also support a wider vision for sustainable transportation, which can be termed "Smart Transportation."

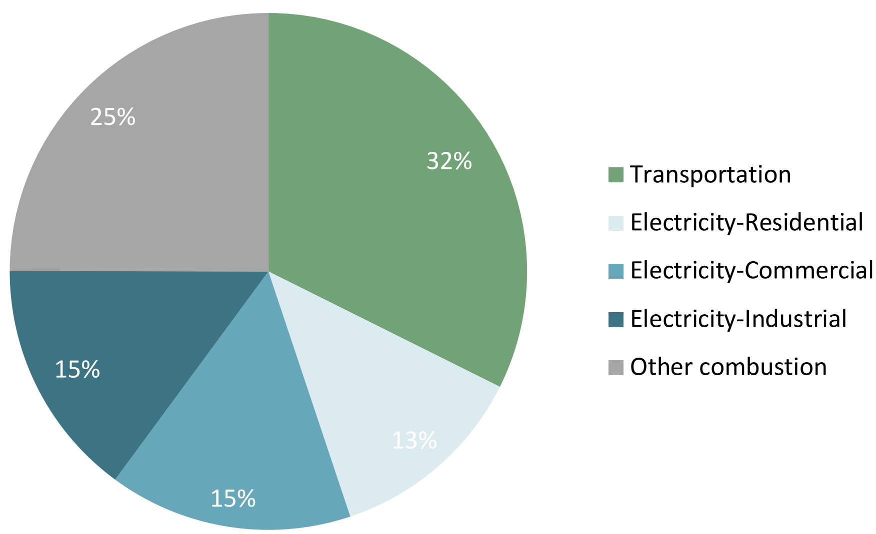
This article outlines how smart, mobile information systems can bring cost-effective, low-carbon solutions to the transportation sector. Then, after outlining plug-in vehicle technologies and environmental impacts, we describe several specific ways in which mobile information can accelerate the success of plug-in vehicles. Finally, we outline how mobile information systems and plug-in vehicles fit into a wider agenda for sustainable and smart transportation.

5A: INTRODUCTION

For the typical American household, the single most environmentally impactful choice that can be made is to buy a more fuel efficient vehicle (Gardner & Stern, 2008). In 2008, the average American household spent $2715 on gasoline and $1353 on electricity (Bureau of Labor Statistics, n.d.), and the transportation sector was responsible for the same amount of greenhouse gas emissions as the electrical sector (Environmental Protection Agency, 2010). Whereas other household carbon- and energy-saving measures (such as eating less meat, switching light bulbs, or reusing shopping bags) require consumers to remember to and choose to change behavior repeatedly and/or in small ways (which has proved extremely challenging), the vehicle purchase decision happens once every few years. Therefore, policies to influence this consumer decision can have a higher impact on national sustainability, per individual decision, than those that seek to change other consumer decisions.

FIGURE 5.13: BREAKDOWN OF US GREENHOUSE GAS EMISSIONS FROM ENERGY, 2008.

Transportation was responsible for 32% of these emissions, compared to electricity's 43%.



In the next several years, policy-makers have just such an opportunity with the arrival of the mainstream electrified, or plug-in vehicle coming simultaneously with the explosion of smart-phone enabled mobile information systems. It is technically feasible for a fully electrified vehicle using energy from 100% renewable resources to completely eliminate greenhouse gas emissions associated with personal vehicle fuel use (emissions would remain from land use impact of roads and sprawl, as well as the construction of wind or solar facilities, etc.). While such a technical potential is years in our future, the tools are at hand to begin rolling out electrified, plug-in vehicles that can save over 50 percent of greenhouse gas emissions from fuel today. The availability of the plug-in vehicles in showrooms reflects many years of work and collaboration between the industrial, political, and environmental sectors. To ensure consumer acceptance and rapid scale up, however, more must be done, and mobile information systems can play a valuable part. These systems can not only enhance the success of plug-in vehicles, but also support a wider vision for sustainable transportation, which can be termed "Smart Transportation."

This article outlines how smart, mobile information systems can bring cost-effective, low-carbon solutions to the transportation sector. Then, after outlining plug-in vehicle technologies and environmental impacts, we describe several specific ways in which mobile information can accelerate the success of plug-in vehicles. Finally, we outline how mobile information systems and plug-in vehicles fit into a wider agenda for sustainable and smart transportation.

5B: LESSONS FROM THE SMART GRID

Leaders in the government and in business have successfully rallied around the concept of the Smart Grid. According to the Department of Energy, the Smart Grid will apply "information-age technologies, such as microprocessors, communications, advanced computing, and information technologies" (Department of Energy, 2008) to improve our existing grid. The Smart Grid can, in the words of President Obama, "save us money, protect our power sources from blackout or attack, and deliver clean, alternative forms of energy to every corner of our nation" (Obama, 2009).

We find that in the transportation sector, which puts a higher monthly fuel cost burden on American families than their monthly electrical bill, the same story can be told about the application of information technology (IT). Applying IT to transportation can replace opacity with real time feedback in topics ranging from traffic to fuel expenditures, and thus increase citizens', businesses', and policy-makers' ability to make more economically and environmentally responsible choices. The tools for such a Smart Transportation system are, literally, already at our fingertips and in our purses. An example is a Virtual Test Drive, which, as we lay out below, uses smart phones to educate citizens about the match between their driving habits and the potential cost, sustainability, and convenience advantages of different plug-in vehicles (See Table 1).

TABLE 5.15: SUMMARY OF THE MAJOR TYPES/CONFIGURATIONS OF ELECTRIFIED VEHICLE

Vehicle type (acronym)	How it works	How to fuel	Range (varies depending on model)	On or near market examples	Availablity date; projected 2011 U.S. production
Internal Combustion Engine (ICE)	Combusts gasoline in engine (this is a traditional gasoline vehicle).	Gas station	~450 mi (gas)	Ford F-150	Now
Hybrid Electric Vehicle (HEV)	Combusts gasoline in engine and recaptures some of the energy otherwise wasted in braking, going downhill. The vehicle stores this wasted energy in a small battery and reuses it later.	Gas station	~450 mi (gas)	Ford Escape Hybrid, Toyota Prius	Now ; 300,000-400,000
Battery Electric Vehicle (BEV)	Converts electricity to motion via a motor. No gasoline or diesel used.	Plug in	~100 mi (electric)	Nissan Leaf, Tesla Roadster Ford Focus EV	Winter 2010 ; ~25,000
Extended Range Electric Vehicle (EREV)	Has both a battery and gasoline engine on board. Uses energy from battery first, then when battery depleted, uses gasoline.	Plug in and gas station	~500 mi (40 on electric, then 450 on gas)	Chevy Volt	Winter 2010 10,000 (60,000 by 2012)
Plug-in Hybrid Electric Vehicle (PHEV)	Has both a battery and gasoline engine on board. Switches between the two fuels depending on driving conditions to optimize efficiency.	Plug in and gas station	~500 mi (gas + electric)	Toyota Prius Plug-in	2011–12 Test run of <1000 in 2011
Neighborhood Electric Vehicle (NEV)	A form of BEV with a smaller battery and limited maximum speed (often 45 mpg). Restricted to low-speed roads.	Plug in	~40 miles (electric)	GEM e6, ZENN	Now ; Unknown production
Fuel Cell Electric Vehicle (FCEV)	Stores energy in the form of hydrogen and uses a fuel cell to convert this energy into motion.	Refuel with hydrogen	Unknown	None	Unknown

The actual range of each type of EV will vary depending on the make and model of the vehicle. Vehicle types highlighted in blue are the main focus of EV policy, business, and development, as well as this article. For ICE example, maybe better to not use a truck as an example? Readers will relate more if you just name a regular car.

5C: SMART TRANSPORTATION RESEARCH AND TECHNOLOGIES

Smart Transportation (and its cousin, Intelligent Transportation Systems or ITS) research has flourished in the past decade. Smart Transportation has many overlaps with ITS, including emphasis on the application of "advanced communications technologies into the transportation infrastructure and in vehicles" (Research and Innovative Technology Administration & Department of Transportation, 2010). But whereas ITS focuses on improvements to transportation safety, service, and efficiency, the term Smart Transportation encompasses a wider reach, including interactions between transportation and other components of life and energy use, as well as improvements to the transportation system.

The majority of research and funding interest in ITS centered on safety applications such as crash avoidance: If two cars know where the other is, they can override the driver in an emergency, and avoid hitting each other. Recently, an interest has emerged in the environmental implications of ITS. Most of this research focuses on better traffic management to reduce congestion and associated waste of fuel. For example, 1.6% of the fuel used in the U.S. (or 2.8 billion gallons) in 2007 was wasted as a result of traffic congestion, up from less than half a percent in 1982 (Schrank & Lomax, 2009). Smart Transportation and ITS have been identified as some of the strongest solutions for this growing problem (Maccubbin et al., 2008). For example, a study in New Mexico found that application of ITS technologies reduced traffic delays by 88 percent, by using techniques such as coordinated traffic signals and better monitoring (Research and Innovative Technology Administration & Department of Transportation, 2010).

In addition, ITS research has expanded to make transit systems more convenient and useful, with the goal of driving up ridership and driving down more fuel-intensive personal vehicle use. The ITS research community has begun to look at ideas that can be implemented soon, even though there are many ITS ideas that cannot be truly implemented until every car on the road has the required technology.

Dozens of examples of implemented and applied smart technologies already exist. The most established example may be real-time feedback displays of fuel economy in vehicles, which can significantly improve fuel economy by altering behavior, as exemplified by the Toyota Prius display (Barkenbus, 2010). Other examples of applied Smart Transportation include Progressive Insurance's "MyRate" program, which installs a telematic device in vehicles in order to refine insurance payments to reflect annual miles traveled and driving behavior (Progressive Insurance, 2010). ZipCar and CityCar have smart-phone enabled vehicle reservation functions (Zipcar, 2010). NextBus sends data on bus arrivals to phones (NextBus, Inc., 2010). GM's OnStar program helps with directions, vehicle maintenance, and emergency support using mobile communications technologies (OnStar, 2010). GoLoco coordinates carpooling between friends (GoLoco, n.d.). Finally, the Department of Transportation, other federal and state agencies, and private entities have deployed an ever-increasing number of traditional ITS programs, from on-ramp timing signals, to centrally controlled traffic lights, remote toll payment systems (such as EZPass, see Figure 2, and real-time traffic and weather feedback systems) (Maccubbin et al., 2008).

FIGURE 5.14: A SMART TRANSPORTATION TECHNOLOGY: EZPASS IN NEW JERSEY.

Ultimately, widespread use and cost-effectiveness of these information technology systems will be greatly expanded if they can leverage existing hardware, or if hardware can be built into the personal and transit vehicles where applicable.

5D: SMART TRANSPORTATION AND ELECTRIFIED VEHICLES

Plug-in vehicles, including plug-in hybrid electric (PHEV), extended range electric vehicle (EREV), and pure battery electric vehicles (BEV), have become the next-generation vehicle of choice for U.S. policy-makers and automakers (Tabuchi, 2009). See Table 1 and cited articles for more details about the differences between these and other plug-in vehicle technologies (Parris, 2006).

While not abundant, efforts to unite these two important, forward-looking trends in transportation (plug-in vehicles and Smart Transportation) have started to emerge, with promising results. The California Department of Transportation commissioned a report on the synergies between ITS and hydrogen vehicles (which are similar to plug-in vehicles) in 2005, which found that synergies could exist, especially in using ITS to support refueling systems for alternative vehicles, as well as coordinating batteries so they could act as storage for the electrical grid (Lipman & Shaheen, 2005). Abdul-Hak and Al-Holou found that plug-in vehicles could optimize energy management in the battery, thereby getting more miles per charge, with predictive knowledge about routes and driving patterns provided by ITS (Abdul-Hak & Al-Holou, 2009).

5D.1: BARRIERS TO PLUG-IN VEHICLES

Two major, education-based barriers confront the adoption of plug-in vehicles. First, citizens lack information about their current driving habits—information necessary to draw the baseline against which the alternatives can be compared. Specifically, drivers do not know their own daily and annual miles driven and fuel expenditures (Turrentine & Kurani, 2007). They are also confused about the implication of comparing one miles-per-gallon (mpg) statistic to another (Larrick & Soll, 2008). Consumers also struggle with the relationship of the mpg "sticker" to real-world fuel economy (Consumer Reports, 2007). This lack of information impedes drivers' ability to make rational economic choices about vehicle purchases (for example, trading off higher upfront costs for improved fuel economy) (Lemoine, Kammen, & Farrell, 2008).

Second, drivers do not yet understand the differences between conventional vehicles, hybrid electric vehicles, plug-in hybrid electric vehicles, and battery electric vehicles. Several studies from academic and industry sources have found that familiarity with electrified vehicle technology, costs, and benefits is significantly lacking (McKinsey & Co., 2010) (Axsen, John, 2008). One study found that stated "high" familiarity with all plug-ins was well under 20 percent, and for PHEVs under 10 percent. Furthermore, they found that accurate understanding of the vehicles may be lower still than stated familiarity (Axsen, John, 2008). This confusion exists despite nationwide political and media interest. To begin with, comparisons of miles per gallon for conventional vehicles and miles per kilowatt-hour for BEV and PHEV vehicles are outside of the experience of virtually all users and, importantly, transportation policy-makers.

Further complicating the education landscape for those who want to sell an alternative type of vehicle is the fact that many consumers are not interested in strict economic rationality when purchasing vehicles: they value nonmonetary attributes more highly (Turrentine & Kurani, 2007). Accurate understanding of these attributes (such as environmental impact) is also undermined by the missing information identified above.

Some research and anecdotal evidence indicates that a multiday test drive is the most effective form of education, allowing users to experience for themselves how the battery wears down, and practice plugging and unplugging the vehicle (Lipman & Shaheen, 2005). However, giving millions of such multiday test drives to users is not economically feasible.

5D.2: VIRTUAL TEST DRIVE

The Virtual Test Drive (VTD) is a mobile device–enabled system that allows users to experience the benefits of a multiday test drive, without the expense. In this way, consumers can build enough knowledge to support a decision to purchase a plug-in vehicle. As described in Figures 3 and 4, VTD highlights the ability of a Smart Transportation application to solve two of the problems described above: to inform drivers about their daily miles driven and fuel expenditures, and to provide a "virtual test drive" to educate them about plug-ins.

FIGURE 5.15: STEPS TO USE VIRTUAL ELECTRIFIED VEHICLE TEST DRIVE.

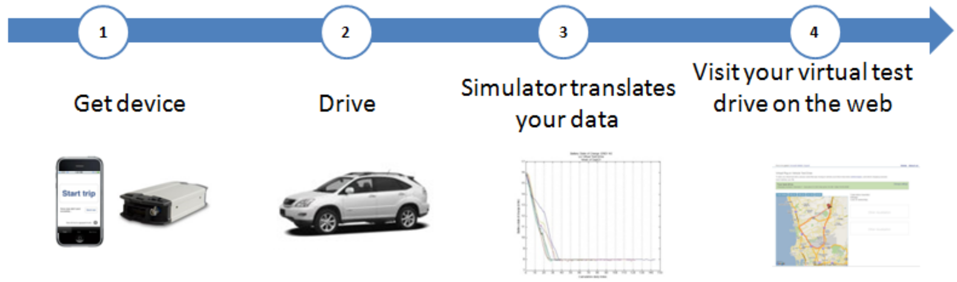
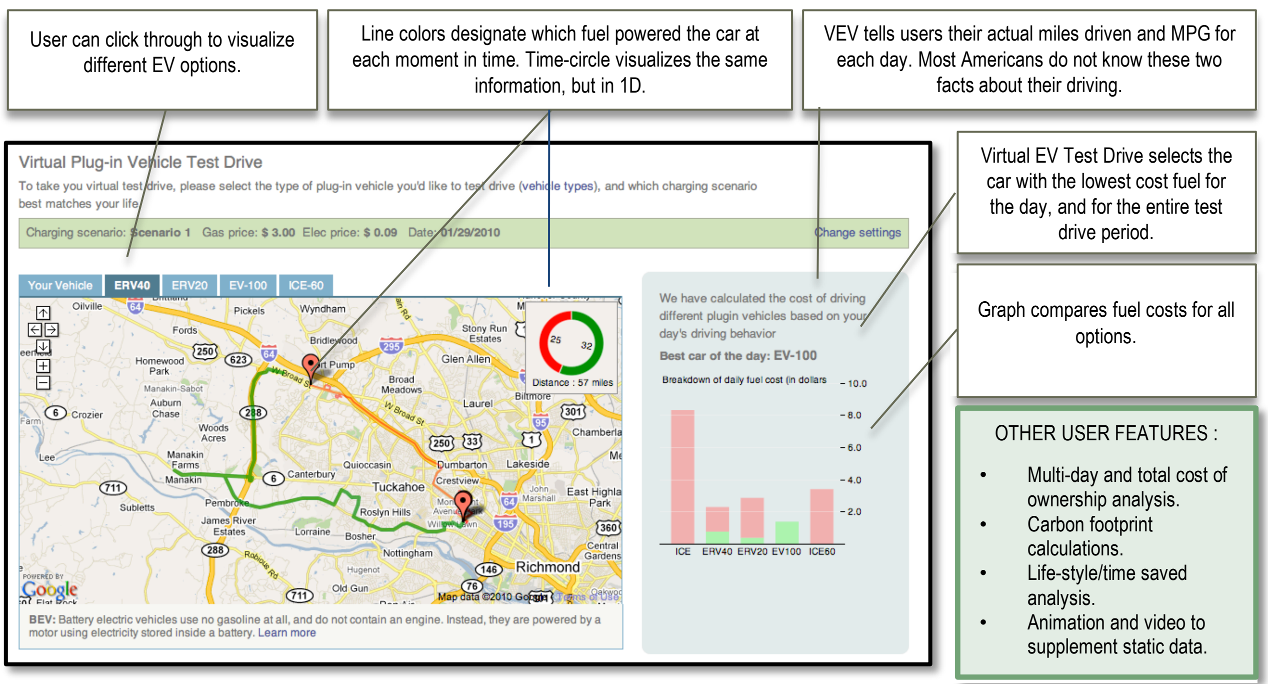


FIGURE 5.16: VIRTUAL EV TEST DRIVE EDUCATIONAL INTERFACE

Users log data from their vehicles, then visit the Web site to learn about how they drive and get recommendations on what vehicles and techniques could reduce gasoline usage, saving money and pollution.



Recent studies have found that education can significantly increase consumer interest in purchasing an alternative vehicle by numbers ranging from 2 to 30 percent (Shaheen, Martin, & Lipman, 2008) (Axsen & Kurani, 2009). In addition, education can "correct" interest from consumers who might be a bad match for a specific plug-in vehicle technology by 20 percent (Axsen & Kurani, 2009). These studies are important indicators, but more rigorous work is needed to better understand the relationship between education and purchasing.

The Virtual Test Drive has five steps, as shown in Figure 3: (1) The driver either downloads the smart-phone application, or installs an off-the-shelf vehicle tracking device. See Table 1 for more on these devices. (2) The driver signs up via Web site, and links Web page to their device. (3) The device sends secure information about vehicle location, speed, and acceleration to a server. (4) The server turns this data into a "drive cycle," which is then used to model how an electrified vehicle would have performed under the same driving conditions. The program has a roster of several different electrified vehicle options for users to explore, to which new vehicles can easily be added, and it can employ a variety of established modeling approaches that range from basic to highly sophisticated route tracking and modeling (Gonder, Markel, Thornton, & Simpson, 2007). (5) The user signs into the Web site to see visualizations of (a) how far they drove that day, (b) how much they spent on fuel on a given day (or month) alongside how much they would have saved in an alternative vehicle, and (c) where a PHEV probably would switch into gasoline mode, and if/where a BEV would have run out of battery (see Figure 4). In this way, VTD uses the characteristics of the Smart Grid—specifically modern, mobile IT and real-time feedback—to educate citizens and support more informed (though not necessarily more economically rational) decision-making on vehicle purchases in the future.

TABLE 5.16: WAYS TO GET SMART-ENABLING DATA FROM INDIVIDUAL VEHICLES TO SECURE SYSTEMS THAT CAN PROCESS THE DATA FOR THE BENEFIT OF INDIVIDUAL DRIVERS AND SYSTEM PLANNERS AND OPERATORS.

Category	Description
In-vehicle mobile systems, installed by the manufacturer:	These devices are installed in the vehicle before purchase. They can read data from the vehicle's on-board computer (including information about engine performance, maintenance, vehicle condition, airbag deployment, etc.). Their capability can be coupled with GPS and a cellular connection. The devices are used for navigation, safety (such as automatically calling emergency vehicles in the case of an airbag deployment), early maintenance warnings, etc. Examples include GM OnStar. The devices usually cost a small fee (as an option at purchase time) and also include a monthly cellular fee to maintain service.
After market on-board diagnostic devices:	These devices can be purchased independently, and installed by plugging into the vehicle's on-board diagnostic port (usually near the left knee of the driver). The devices sometimes include GPS and cellular signaling technology. The devices are used to log data about engine performance and maintenance issues. Some insurance companies have begun to place them in cars to enable pay-per-mile insurance, as well as to develop rates based on safe driving characteristics. Many commercial fleet operators use these to track company cars' and drivers' performance and location. Devices can cost between $50 to $600 (depending on presence of cellular and GPS capabilities) as well as a monthly cellular service fee.
Smart phone apps:	Most smart phones (such as the iPhone, Android, or Blackberry) contain GPS and accelerometer capabilities, allowing them to provide the locational services associated with the above devices. In addition, several devices exist that can plug into a vehicle's on-board diagnostic port and send a wireless signal to a smart phone. The smart phone then links the data with the relevant GPS coordinates and can send the data using the phone's existing cellular contract. Several apps have emerged for Smart Transportation using both the location/accelerometer features alone, or combining them with the wireless connection to the vehicle's computer. Apps cost anywhere from zero to $20, and wireless on-board transmitters cost from $50 to $200.
Remote sensing devices	These devices sit in a vehicle and are logged when the vehicle passes close by a sensor. The most common example is EZPass or FasTrak devices that log when an individual car goes through a toll booth for automatic tolling. Devices cost little money, and usually have no associated fees (beyond, of course, the tolls).

5E: ENVIRONMENTAL IMPACTS OF EVS

What would selling more EVs do for the climate? The answer depends on several factors, including the vehicle displaced by the EV, the environmental impact of the battery, and what type of generator makes the electricity. EVs reduce greenhouse gas emissions under every set of reasonable near term assumptions, and they always save oil. But the magnitude of savings is important to understand when deciding whether or not to buy (at a personal level) or support (at a political level) a plug-in. In general, plug-in vehicles save greenhouse gases in three ways:

1. In the vehicle, electricity can be converted to motion at about 80 percent efficiency. Gasoline can only be converted at 30–40% efficiency.
2. It is more efficient to process and send electricity through wires than it is to process and ship/pipe gasoline.
3. Some electricity is lower carbon (natural gas) or no carbon (wind or solar).

When studying the impact of any vehicle, it is important to consider the impact of driving the car, the impact of building the car and its components, and the impact of consequences of driving the car such as additional road construction or encouraging people to live far away from their work (Chester & Horvath, 2009). Greenhouse gas impact, the focus of this section, is measured in carbon dioxide equivalents, or CO_2-eq, with a time horizon of 100 years, using values recommended by the Intergovernmental Panel on Climate Change (Metz, Davidson, Bosch, Dave, & Meyer, 2007).

5E.1: MANUFACTURE

We assume the process and related emissions needed to construct a conventional car, a hybrid, or an EV are the same, excluding the battery (Chester & Horvath, 2009). EVs, however, have an additional environmental burden from lithium ion battery manufacture. The impact of the battery will vary depending on how big it is, what fuels are used to power its production (often a function of where the battery is manufactured), and if the battery comes from virgin or recycled material. We use an average of 120 kg CO_2-eq per kilowatt hour (kWh) of energy capacity in the battery (Samaras & Meisterling, 2008). Battery size in EVs will range from 5 kWh for hybrid applications to ~50 kWh for high performance battery electric vehicles.

5E.2 FUEL AND OPERATIONS

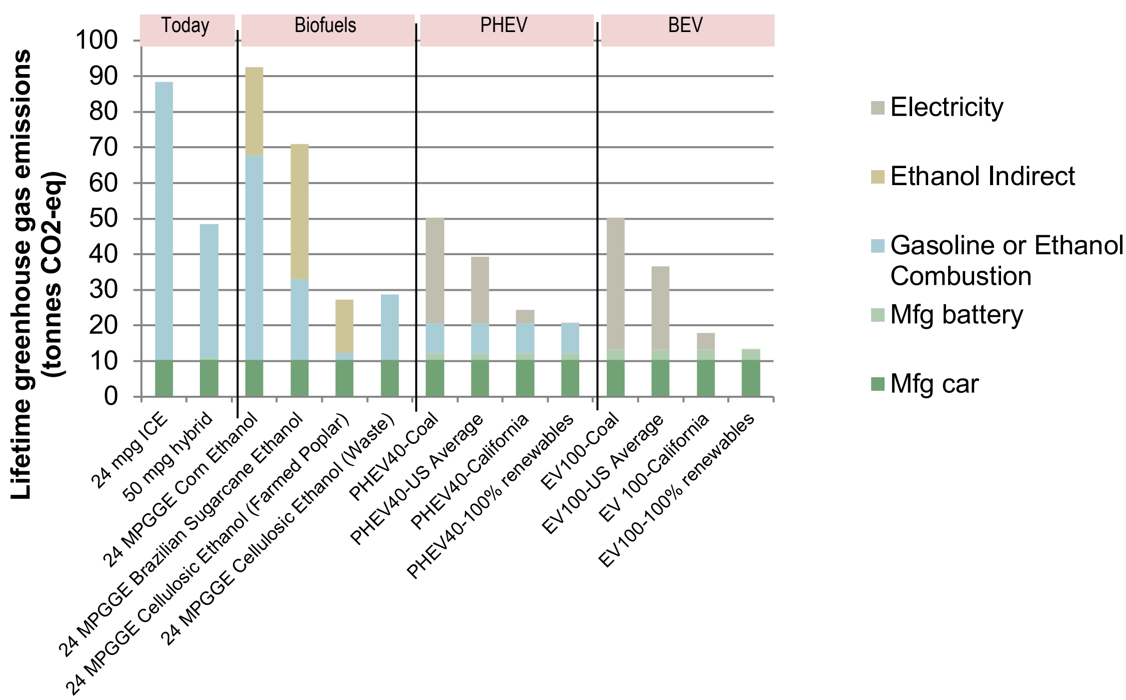
We consider vehicles powered by gasoline, electricity, or a mix of the two. Burning a gallon of gasoline creates about 9 kg of CO_2-eq, while transporting and refining that gallon creates about 1.7 kg (Chester & Horvath, 2009). With today's average U.S. generation mix, electricity creates about ~600 grams CO_2-eq per kWh delivered to the plug, whereas in California, where the mix has lower carbon intensity (utilizing more hydro power and natural gas), each marginal kWh only creates ~330 grams of CO_2-eq (Elgowainy, Burnham, Wang, Molburg, & Rousseau, 2009). If electricity came purely from coal (which it does not anywhere in the U.S.), it would create ~950 grams of CO_2-eq. Electricity from renewable generation causes just over 0 grams, because manufacture of the wind turbines or solar panels must be taken into account.

Finally, we combine these assumptions to calculate the total lifetime greenhouse gas emissions from five different types of vehicles: an average U.S. car that gets 24 mpg, a car that gets 24 mpg of gasoline equivalent but runs on ethanol, a 50 mpg hybrid vehicle (that does not plug-in), a plug-in hybrid vehicle with a 40-mile electric range, and a battery electric vehicle with a 100-mile electric range. We assume that the plug-in hybrid is in electric mode 80 percent of the time, and that the other 20 percent of the time, the car gets about 45 mpg. We modeled the PHEV and the EV under four electricity scenarios each: 100% coal, the 2010 average U.S. fuel mix, the 2010 fuel mix for California (which has a about half the greenhouse gas intensity as the U.S.), and 100 percent renewable fuels. As shown in Figure 5, the EVs always save greenhouse gas emissions compared to the average U.S. vehicle; fuel-use savings more than offset additional emissions from the battery manufacture. In addition, the CA and 100 percent renewable EVs have comparable or better emissions compared to the most advanced cellulosic ethanol vehicles (which are not yet commercially available). Data on carbon intensity for ethanol, both direct (combustion) and indirect (land impacts) emissions, as well as California electricity, were taken from the recently published Low Carbon Fuel Standard in California (California Air Resources Board, 2009).

Figure 5 also indicates that (A) the displaced vehicle matters, and next to a hybrid the PHEV40 does not save many greenhouse gas emissions, and (B) using cleaner electricity (such as electricity in California) does impact the lifetime savings significantly. In the worst case scenario, using 100 percent coal for the electricity, the plug-in vehicles break even with a non-plug-in hybrid vehicle. The literature cited in the preceding paragraphs contains much more technical discussions of lifecycle impacts of various vehicle types, for those interested in other nuances.

FIGURE 5.17: COMPARISON OF LIFETIME GREENHOUSE GAS EMISSIONS FROM DIFFERENT TYPES OF VEHICLES (~150,000 MILE LIFETIME).

EV greenhouse gas benefit depends on the comparison vehicle and the carbon content of the electricity it uses.

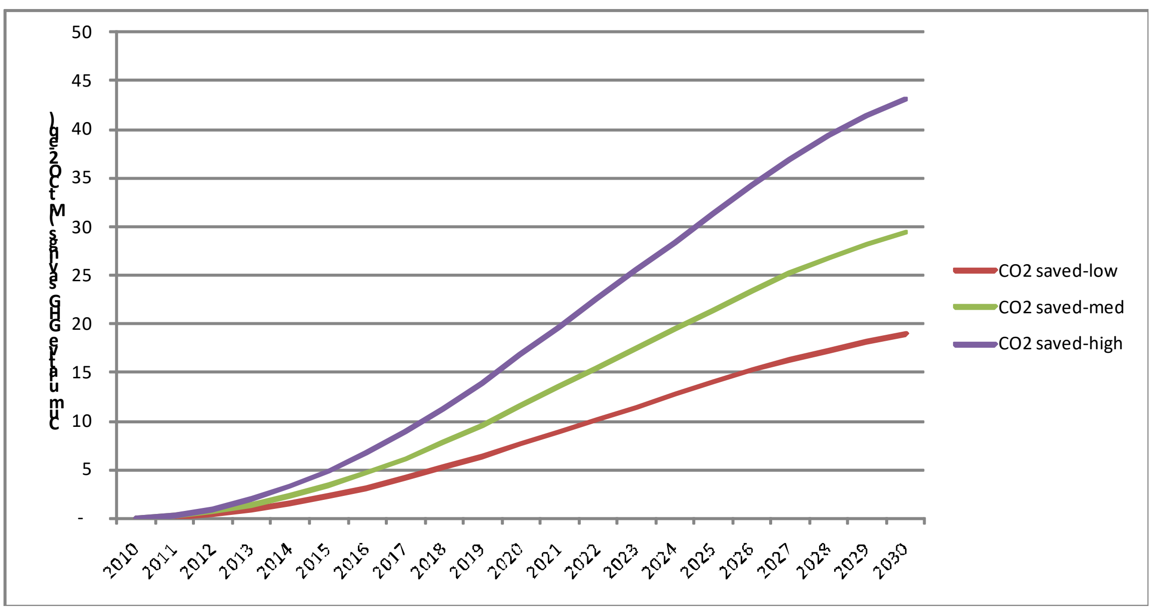


Points A and B are critical when modeling the greenhouse gas savings of a large number of plug-in vehicles in the future (Natural Resources Defense Council & EPRI, 2007). It is impossible to accurately predict how many plug-in vehicles will be on the road 10 years from now, because no mainstream vehicles have even hit the road, and policy, technology, and consumer reaction from drivers have yet to unfold (though this has not stopped plenty of groups from to make those predictions). We use a reasonable estimate based on a report written by the Electrification Coalition: five percent of the light duty vehicle fleet, or just over 11 million plug-in vehicles (half fully electric, half partially electric and partially gasoline), will be sold between 2011 and 2020 (Electrification Coalition, 2009).

Figure 6 first mention shows the greenhouse gas impacts of these vehicles under three scenarios. The medium case assumes that the plug-ins displace the average new car, which we pin to the Corporate Average Fuel Economy (CAFE) standard for each year, that carbon intensity of the U.S. grid decreases by 1 percent per year, and that plug-ins drive 80 percent on electricity. The high case assumes that the plug-ins displace cars 20 percent less efficient than CAFE, that the grid intensity decreases by 3 percent per year, and that plug-ins drive 90 percent on electricity. The low case assumes that the plug-ins displace vehicles that are 20 percent more efficient then CAFE, grid intensity stays the same, and plug-ins drive 70 percent on electricity. In all cases, we assume that one-third of the plug-in vehicles are sold in California. The high savings case also results in 80 million barrels of oil saved by 2020. We assume that sales stop for our fleet of 10 million after 2020, but that those vehicles continue to save greenhouse gas emissions until the end of their lifetimes.

FIGURE 5.18: CUMULATIVE GREENHOUSE GAS EMISSIONS SAVINGS FROM A FLEET OF 11.2 MILLION EVS SOLD BETWEEN 2010 AND 2020 UNDER THREE SCENARIOS (5% OF CURRENT FLEET).

Maximum cumulative savings are ~45 M metric tonnes of greenhouse gas emissions. In 2009, the U.S. emitted ~ 7000 M metric tonnes.



Smart Transportation can help push plug-in vehicles to the "high case": With better information about routing and driver habits, the vehicles' computers can learn to optimize battery usage. In addition, Smart Transportation technologies and communications infrastructure could enable smart charging (having the vehicle charge at times that put minimal stress on the grid) or "vehicle to grid" often called V2G (Sioshansi & Denholm, 2009). In V2G, vehicles act as storage for the grid while they are parked, giving electricity back to the grid when it needs more, and filling up the battery the rest of the time. Smart charging and V2G can both help integrate variable renewables, such as wind, on to the grid, by toggling their charging patterns to match the rise and fall of the renewable resource.

We assumed that the road infrastructure and other upstream environmental costs are exactly the same for a gasoline vehicle and any plug-in vehicle. However, if plug-in vehicles cause people to buy cars who previously would have ridden transit or walked, or cause people to drive more miles per year because of lower operating costs, then this assumption would have to be revisited. It is more likely that individuals in nations that do not have fully mature automotive markets (like India or China) would fit the former case (lower operating cost for vehicles would cause more car ownership).

The latter case, often called the Jevons Paradox or rebound effect, reflects the worry that if driving becomes cheaper because of cheaper fuels like electricity (or less guilt-inducing, because of plug-in vehicles' lower carbon footprint), then people will react by driving more, thereby keeping the actual financial and greenhouse gas costs the same. The Jevons Paradox is named after William Stanley Jevons who, in 1865, wrote a book exploring the relationship of coal use and steam engine productivity. The Paradox is debated by economists, and most agree that the evidence is not strong enough to claim that all energy efficiency improvements "will increase energy consumption above what it would have been without those improvements," though they also agree that it is a phenomenon that deserves more attention (Sorrell, 2009). Furthermore, in theory, vehicles may be a special case: While reducing the fuel cost per mile saves money, increasing the amount of driving per day may not actually increase the "useful work" done by the vehicle (most people do not want to spend more time in the car) (Sorrell, 2009). This is different than, say, a steel production plant where it would be more useful to produce more steel for the same amount of money. However, savings on vehicle fuel could have indirect rebound effects, perhaps encouraging the owner to take a vacation to Hawaii, which is very energy intensive (Madlener & Alcott, 2009).

Other studies have looked at data (as opposed to theoretical models). Schipper and Grubb found that in transportation, though the U.S. and Canada experienced significant increases in vehicle fuel economy between 1973 and 1995 (30%), drivers showed little change in activity, indicating that in these countries, very little rebound affect appears to have occurred (Schipper & Grubb, 2000, 2000). The rebound effect for transportation was lower than for other sectors (such as industrial efficiency or home electricity use). Other empirical studies have found similarly small increases in miles driven for U.S. drivers reacting to lower cost-per-mile of driving (Greene, 1992). Recently, one study suggested the rebound effect for personal vehicles declines substantially with increased income, and is therefore smaller today than in decades past, and likely to get smaller still as wealth in the U.S. continues to grow (Small & Van Dender, 2005). Therefore, we assumed no rebound affect for our analysis, which is concerned with the U.S. This assumption, like the assumption that plug-in vehicles will cause no current walkers/cyclists/transit riders to buy a car, would have to be revisited for other countries, especially lower income countries.

5F: A PRESCRIPTION FOR POLICYMAKERS

Plug-in vehicles can significantly reduce the environmental impact of personal vehicle use. Mobile information systems can, as shown by the examples above, increase the likelihood of success for plug-in vehicles, and enhance their ability to save greenhouse gas emissions, by avoiding stranding users who have run out battery, optimizing energy use in the vehicle by knowing where the vehicle is going on a given day, and other techniques described above. Certainly, there are hurdles to Smart Transportation, including (like the Smart Grid) the challenges of implementing adequate privacy protection. And certainly, more education will not cause all citizens to start to behave with textbook economic rationality with regard to vehicle purchases. Even taking these limitations into account, Smart Transportation will help drivers motivated primarily by economics to improve their budgeting, and help other drivers explore options that coincide with their values, such as environmental sustainability or convenience.

Implementing Smart Transportation can help save money and reduce oil use and greenhouse gas emissions by increasing the flow of information about transportation to consumers and policy-makers. It can also enable the penetration of new technologies, such as plug-in vehicles. Furthermore, it can support changes that are just as, if not more, important than plug-in vehicles: more carpooling, transit, and walking/biking. The U.S. can leverage existing infrastructure (smart phones) to "retrofit" existing cars, roads, and transit routes, and automakers have already started to build smart capabilities into new cars.

To enable Smart Transportation and its intersection with plug-in vehicles, federal, state, and local policy-makers should focus on several issues:

1. Support the build-out of an appropriate infrastructure to fuel new types of vehicles, and record data along roads. On charging infrastructure for refueling, it may be more important to streamline the process of installing charge stations than to subsidize the costs (McKinsey & Co., 2010).
2. Support research and infrastructure that enable plug-in vehicles to drive as many miles as possible in "electric" mode, while keeping costs low. These include route planning and optimization, citizen education about plug-in vehicles, smart charging, and strategically located charging stations. All three enablers leverage Smart Transportation technologies, including telemetry and other communication of data.
3. Make the grid as green as possible. Plug-in vehicles engaging in Smart Charging or V2G can support a greener grid, with appropriate advances in research, demonstration, and regulation.
4. Help automakers manufacture plug-in vehicles and components, through subsidy and encouraging more flexible, advanced manufacturing techniques.
5. Do not neglect walk-ability, bike-ability, transit, and smart growth strategies for the sake of more efficient vehicles. Efficient vehicles are necessary to meet our greenhouse gas emission reduction goals for transportation, but they are not sufficient. Non–personal vehicle transportation warrants just as much research and policy support as plug-in vehicles, and it can also be enhanced by Smart Transportation technologies.</NL>

Implementing Smart Transportation can bring many of the same types of efficiency and advanced technology benefits as the Smart Grid. Transportation, which has a similar greenhouse gas burden and higher household financial burden on the U.S. than electricity, deserves the same attention as the Smart Grid. EVs, which hit mainstream showrooms early this winter, are an opportunity to realize a significant step towards transportation sustainability, and they demonstrate the potential benefits of Smart Transportation. The integration of mobile information and transportation to support plug-in vehicles is one important example of the wider potential of Smart Transportation to increase the sustainability of how goods and people move from place to place.

CHAPTER 5: ACKNOWLEDGEMENTS

The authors would like to acknowledge the Energy Foundation, the Karsten Family Foundation, and the Berkeley Fellowship for Graduate Study for their support. We thank Nate Holtman and Chris Jones for their help and comments.

6: THE TRANSPORTATION LEAPFROG: USING SMARTPHONES TO COLLECT DRIVING DATA AND MODEL FUEL ECONOMY IN INDIA

CHAPTER 6: PREFACE

In the following chapter, I, along with LBNL scientist Anand Gopal supported by Amol Phadke and Sam Saxena, put the theory of Chapter 5 into practice. Use new data collection tools, in this case, a smartphone app acting as a very granular GPS-enhanced travel diary, we collect data about granular driving conditions in Pune, India. We then explore how this type of work could apply to broader EV preparedness in local contexts. This work is published verbatim as an Lawrence Berkeley National Lab Report LBNL-6293E under the same title with minor edits to adapt the formatting to match other chapters (Gopal, Schewel, & Phadke, 2013). I reproduce it here with the consent of my co-authors.

CHAPTER 6: ABSTRACT

Car ownership in India is expected to skyrocket in the coming decades, strongly driven by rising incomes. This phenomenon provides unprecedented opportunities for automakers and equally unprecedented social and environmental challenges. Policymakers, urban planners and civil society see this car boom leading to an explosion in problems related to congestion, infrastructure, air pollution, safety, higher oil imports and climate change. For all these stakeholders to take effective action, good data on how people use their cars, their demand for mobility and their behavior in mobility is essential. Unfortunately, there is very little data on the Indian transport sector as a whole and virtually none on real-world vehicle performance and use. The rapid development of high quality mobile telecommunications infrastructure provides India with the opportunity to leapfrog the West in cheaply collecting vast amounts of useful data from transportation. In this paper, we describe a pilot project in which we use commercial smart phone apps to collect per second car driving data from the city of Pune, instantly upload it through 3G and prepare it for analysis using advanced noise filtering algorithms for less than $1 per day per car. We then use our data in an Autonomie simulation to show that India's currently planned fuel economy test procedures will result in over-estimates of fuel economy of approximately 35% for a typical Indian car when it is operated in real world conditions. Supporting better driving cycle development is just one of many applications for smart phone derived data in Indian transportation.

6A: INTRODUCTION

Car ownership in India is expected to skyrocket in the next two decades (Clemente, 2011). India is projected to become the world's third largest auto market after the US and China by 2030 and possibly overtake the US by 2035 (Booz-Allen Hamilton, 2011). Most importantly, this demand is primarily due to rising incomes and cannot be easily averted through aggressive Avoid-Shift (A-S) policies because car ownership is dictated by more than a simple desire for convenient mobility (Wolfram, Shelef, & Gertler, 2012). Automakers recognize the huge emerging market both in India and China and are gearing up to supply them. However, if the car ownership projections come true, India alone will be responsible for almost 8% of global transportation greenhouse gas emissions by 2030 (Fulton, Cazzola, Cuenot, Kojima, & Onoda, 2009) (World Business Council for Sustainable Development, 2004) and will need to import more than 85% of its crude oil (Clemente, 2011). In addition, India already has the highest annual road accident deaths in the world (World Health Organization, 2009), some of the world's worst air pollution from transport, and severely underdeveloped transport infrastructure (The World Bank, 2002). Thus, the social and environmental externalities from this car boom need to be aggressively and cost-effectively mitigated starting immediately. To design effective measures policymakers, academics, urban planners and civil society need excellent data from Indian transportation. Unfortunately, there is very little macro data on the Indian transport sector (International Transport Forum, 2010) and virtually no useful data on mobility behavior and demand (Fulton et al., 2009) (Ramachandra & Shwetmala, 2009).

The traditional approach to transport data collection follows a hardware intensive approach with installation of on-road sensors, laser and vehicle monitors, specialized in-vehicle loggers, etc. Developed nations such as the U.S. have invested tens of billions of dollars in such data collection infrastructure for transportation (Staples, 2006). Current hardware approaches are very expensive. In the US, each traffic monitoring device to be used on a single intersection costs between $2,000 (for a simple loop traffic counter) and $24,000 (for machine vision), plus installation costs and $2,000-$4,000/year for maintenance (US Department of Transportation, 2012). These costs do not include the installation and maintenance of a data management system. India had approximately two million kilometers (km) of paved roads in 2008, according to the World Bank (World Bank, 2012). If just 20% of these kilometers were monitored for simple vehicle speeds and counts, the hardware costs would rise to $4 Billion (assuming an average of $10,000/device and one device per km).

India does not have the time, or the capital resources, to follow such a hard path that collects only rudimentary information. Fortunately, the extremely rapid development of India's mobile telecommunications infrastructure provides us with the opportunity to get even better transportation data than traditional approaches at much lower costs. Several states within the U.S. have found that the costs of using vehicle probes (dedicated vehicles, usually commercial, with installed speed monitoring equipment) are about one-fifth to one-fourth that of dedicated hardware. In this paper, we describe an innovative transport data collection framework that is cheaper and able to gather more data than the probe vehicle approach. Our approach piggybacks on the great Indian telecommunications leapfrog (The World Bank, 2008) (McKinsey & Co., 2006),to catalyze an equally significant leapfrog in transportation data acquisition and analysis. Specifically, we describe the technical and economic details of a pilot project in which we use commercially available smart phone apps to collect per second data on speed, acceleration, GPS location and inclines for cars in the city of Pune that is instantly uploaded by 3G and then prepared for analysis using advanced noise filtering algorithms.

The data we collect has numerous applications that range from systems engineering design of automobiles to urban transportation planning and management. In this paper, we choose to highlight an application that can substantially improve the labeling test procedure for India's proposed passenger car fuel economy standards (Bureau of Energy Efficiency, Government of India, 2011). We use our speed-time driving profiles from Pune, a large Indian city representative of traffic and infrastructure conditions where most of India's passenger car miles will be logged over the next two decades, and compare it with the Modified Indian Driving Cycle (MIDC), the currently designated test cycle that is not based on actual Indian driving data, but instead is a lightly modified European drive cycle (Chugh et al., 2012). We find that the smart phone derived real world driving profiles, which cover both urban and suburban trips, on average show substantially sharper and more frequent acceleration and braking in addition to much longer idling times. In order to demonstrate the implications of this for the fuel economy labels, we simulate the performance of a low-powered compact model most representative of models that will dominate future Indian sales, in Autonomie, a widely used powertrain simulation program. We find that the current test procedures could overstate fuel economy values by approximately 35% relative to real world performance. India chose to use the MIDC, which is derived from the New European Driving Cycle, for reasons that are not entirely clear. We surmise that the development cost must have been a factor. Regardless of the historical reasons for the choice of the MIDC, we show that by employing smart phone based driving cycle development techniques, India can develop a much more appropriate test cycle cheaply.

In addition to the specific policy application we highlight in this paper, the uses of vehicle specific smart phone based data can support a wide range of critical transportation planning, engineering and policy decisions. Some examples include the use of smart phone derived data to:

- Employ a systems-based, bottom-up engineering design of automobiles for Indian traffic, consumer preferences and the regulatory environment.
- Develop a multi-modal, multi-sectoral transport energy demand and emissions model for India.
- Plan public transportation infrastructure based on mobility demand in key corridors.
- Plan highway and road infrastructure.

In our research group at UC Berkeley and Lawrence Berkeley National Laboratory we plan to use our innovative data collection and analysis techniques for several similar applications. We also note that the same key factors hold true in much of the rest of the developing world - poor transportation data along with excellent, affordable mobile telecommunications infrastructure. Hence, the techniques we highlight here can be deployed to solve transportation problems in other major emerging regions like China, Latin America, Southeast Asia and Africa.

6B: METHODS

6B.1: SMART PHONE DATA COLLECTION

Our smart phone derived data collection approach can be used in a variety of contexts for a variety of applications. We can collect speed, location and acceleration data for an individual person across all modes that he or she uses in a given time period. Smart phone derived data collection for transportation has become increasingly popular. Much recent work has focused on using the smart phone to both collect data, and deliver feedback to an individual. Specific examples include modeling vehicle electrification impact for individuals (Schewel & Kammen, 2010), feedback to show the cost and carbon benefits of transit ridership (Winters, Barbeau, & Georggi, 2008), and the replacement of in-vehicle navigation systems with smart phones ("App Store—TomTom U.S.A.," n.d.).

In addition, other researchers have used smart phone based data collection to support better understanding and management of transportation systems. Recent examples include using cell signals to monitor the timeliness of transit (Beutel & Association for Computing Machinery, 2010), using a fleet of smart phone probes to monitor real-time traffic conditions (Herrera et al., 2010), planning bike routes (Charlton, Hood, Sall, & Schwartz, 2011), and using smart phone-based approaches to enhance or displace household travel surveys (Nitsche, Widhalm, Breuss, & Maurer, 2012) (Bohte & Maat, 2009).

Our methodology for data collection most closely resembles that of Charlton and Schewel in that we utilized commercial smart phones with dedicated data-collection apps, and analyzed the movements of distinct devices (as opposed to groups of devices like Herrera and Thiagarajan). Unlike the travel survey work, we did not supplement smart phone data collection with surveys for the participants. Finally, as explained below, the applications we describe in this paper do not need locational data, though the app is capable of collecting it. Our app is also capable of harvesting all the data gathered by the vehicle's onboard computer.

For this pilot study, we selected three participants in Pune, each with a slightly different mix of urban and highway routes in their daily car commute, who already owned their smart phones. We asked each participant to install an existing Android app (specifically, Google MyTracks) (Google, 2012). Each phone was configured for one second trip data collection of time stamp, speed, altitude, and accuracy sensitivity. At the start of each trip, the participant turned on the app and initiated recording. The app recorded trip data every second and uploaded to our server in Berkeley, CA every time 3G connectivity was available. When the trip was complete, the participant stopped the recording. We recorded five morning and evening commute trips by each participant, totaling over 350 km of travel.

Table 1 shows the breakdown of data collection costs in the pilot project and compares those with the costs of using a dedicated hardware approach. If the cost of purchasing the phone is excluded since our participants already owned one, the overall cost of collecting the data for one month was less than $1.00 per vehicle per day, without including research labor. Even if we had to purchase a smart phone just for this effort, the total cost of just using that to collect trip data would still less than $5/day, much lower than using a specialized, in-vehicle data logger, which costs between $200 and $1000 for vehicles in the US, plus a unique monthly data subscription (Frost & Sullivan, 2011) (German, 2012). The phone we priced is the Samsung Galaxy Y S5360 ("Samsung Galaxy Y S5360: Price in India, Reviews, Specification.," 2012), which is almost twice the price of the cheapest Android on the Indian market. However, the Galaxy Y S5360 is the most affordable Android on the Indian market with a GPS, accelerometer and battery life of the necessary quality and reliability for our work.

TABLE 6.17: DATA COLLECTION COSTS IN PILOT PROJECT. THESE FIGURES EXCLUDE SERVER COSTS AND SET UP/PROCESSING ENGINEER COSTS WHICH WOULD BE COMPARABLE FOR THE TWO DATA COLLECTION APPROACHES

Cost Component	Pilot Study Cost (US$)	Cost of Traditional Dedicated Hardware Approach (US$)
Cost of Phone/GPS device	$140 OR $0 if leveraging existing phones	$600
Cost of 3G Data plan/month	$4.5 for dedicated plan OR Less than one percent of one cent per day if data plan already exists and new geo data is incremental	~$18/month
App cost	$1.99	$0
Total Cost for one month of data collection for one user	Between $2 and $150	$620

The benefits of our method were the low cost, the ease of installation, and the high accuracy and time rating of the data. The main detriment was the fact that test subjects often forgot to trigger the app to start recording information at the start of each trip (and stop at the end of trips). In order to mitigate this, which would be necessary to use this scheme a large scale, we are developing a specialized app that turns on automatically during travel (either by sensing movement or by permanent installation in the car, connected to the power source, and recording whenever the car is turned on).

It is important to note that this pilot project was undertaken with minimum funding to demonstrate the low cost, feasibility and overall ease of smart phone based transport data collection in a developing country where there are no other means of obtaining such data.

Further, we collected our data without any need for expert labor; we simply emailed instructions to the participants on how to install and use the app. Other studies that develop driving cycles involve the extensive use of expert labor whether using a chase car approach or in-vehicle logging. However, we are aware that the study design is not robust enough for the driving profiles we develop from our data to be distilled into a representative Pune driving cycle. We make no such claim but we do gather driving data from within the vehicle during peak hours that include several of the city's main arterials. As a result, the data we collected is sufficiently representative of peak hour commuting in Pune to provide us with insight into the real-world fuel economy performance of a typical Indian car. In the next stage of this project, we will design a robust study that takes into account the most heavily traveled routes by cars across all the major regions of the country and includes a large enough sample to develop an Indian Driving Cycle that is best representative of Indian driving behavior, traffic and car use. In this larger effort, the data collection method will be identical to this pilot project.

6B.2: DATA CLEANSING AND DRIVING PROFILE DEVELOPMENT

We cleansed the data to exclude data points with very poor accuracy ratings. In addition, we analyzed the data to look for improbable changes in speed (going from 0 to 25 m/s in two seconds, for example) and smoothed those incidents to represent reasonable speed changes for a vehicle.

Once the data was received in the server and filtered, we analyzed all trips in each commute type to create three Pune driving profiles, comprised of the time variation of speed, acceleration, and grade:

a. **Pune 1** and **Pune 3** represent commutes 100% on city roads in a mix of heavy and light traffic conditions.

b. **Pune 2** represents a commute which is predominantly highway driving

The app collected time stamp, speed, bearing, and altitude. We derived the components of each driving profile from the Smart Phone data as follows in Equations 1-5:

EQUATION 6.13-5: DRIVING PROFILE DERIVATIONS FROM SMARTPHONE DATA

- Timestep (seconds): $\Delta t = timestamp_{previous\ record} - timestamp_{current\ record}$
- Speed (meters/second) $= recorded\ by\ device$
- Acceleration (m/s/s) $accel = \frac{speed_{previous\ record} - speed_{current\ record}}{\Delta t}$
- Change in altitude: $\Delta alt = alt_{previous\ record} - alt_{current\ record}$
- Grade (degrees): $grade = \arctan\left(\frac{\Delta alt}{speed * \Delta t}\right)$

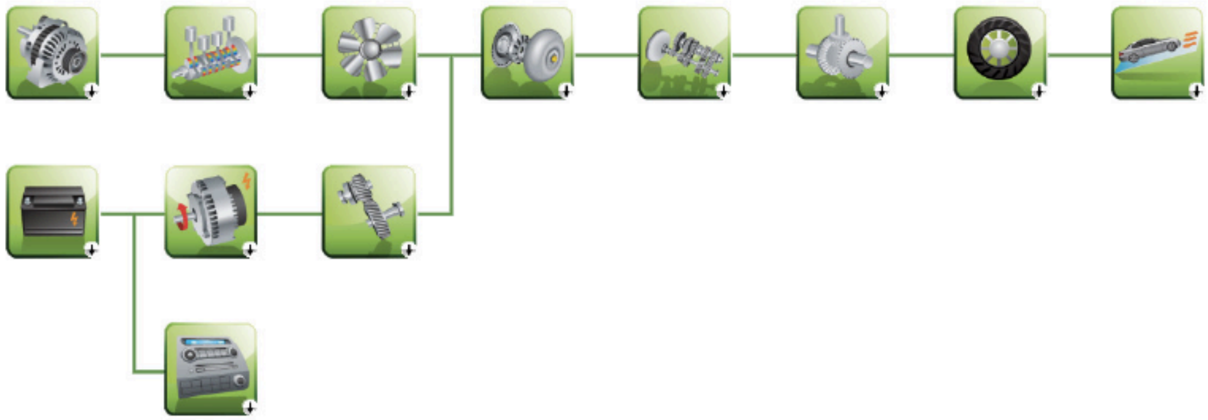
Next, we simulated the performance of a typical Indian compact car on each of the three driving profiles we derived and on the MIDC.

6B.4: AUTONOMIE SIMULATION

Simulations were performed using the powertrain simulation tool, Autonomie ("Autonomie—Overview," n.d.). Autonomie combines physics and mathematics based submodels of individual powertrain components with models of the vehicle propulsion controller, and models of driver and environmental factors to create an overall powertrain model capable of predicting the performance of a vehicle under specified conditions. Drive cycles are specified as vehicle speed and grade profiles versus time. Major component submodels (such as the engine, batteries, transmission, etc.) use experimental measurements to specify performance and efficiency maps spanning the full range of possible operation for a component, however these maps can also be created using detailed modeling tools (for instance, using GTPower ("GT-POWER Engine Simulation Software," n.d.) for engine modeling).

A vehicle model was constructed for a conventional internal combustion engine vehicle resembling a Maruti Swift (most representative of the dominant models in the current and projected Indian fleet mix). The vehicle engine has a maximum power of 64 kW, a gross weight of 1415 kg and a 5-speed transmission, with gear ratios and a final drive ratio similar to those in a Maruti Swift. FIGURE 1 shows the interface of component submodels that make up the full vehicle powertrain model.

FIGURE 6.19: DATA COLLECTION COSTS IN PILOT PROJECT. THESE FIGURES EXCLUDE SERVER COSTS AND SET UP/PROCESSING ENGINEER COSTS WHICH WOULD BE COMPARABLE FOR THE TWO DATA COLLECTION APPROACHES FROM LEFT TO RIGHT AND TOP TO BOTTOM: STARTER MOTOR, ENGINE, MECHANICAL ACCESSORIES, TORQUE CONVERTER, TRANSMISSION, DIFFERENTIAL, WHEELS, CHASSIS, BATTERY, ALTERNATOR, TORQUE COUPLING AND ELECTRICAL ACCESSORIES.



6C: RESULTS

6C.1: COMPARISON OF PUNE DRIVING PROFILES AND THE MIDC

Figure 2 compares the speed-time profiles of the three Pune driving profiles we developed from our data and the MIDC. The first 800 seconds of the MIDC is meant to represent city driving. When you compare this segment of the graph with the two city profiles from our data, Pune 1 and Pune 3, the differences between them and the MIDC are even stronger than we anticipated. Table 2 shows that the braking and acceleration events are substantially more frequent in Pune 1 and Pune 3 but each of these events are also much sharper than for the MIDC. Pune 1 is city driving in light, off-peak traffic and still shows almost as much stopping as the MIDC. In peak city traffic, represented by Pune 3, where the majority of car miles are logged, stopping is almost 8 times more frequent than the MIDC.

Finally, it is instructive to compare the highway driving representation in the MIDC and the Pune 2 profile, which is our highway profile. Figure 2 shows that Pune highway driving has almost no correlation with the MIDC's highway segment. There is no cruising in Pune 2 and the stop frequency is higher than in the highway portion of the MIDC. Table 2 shows that the magnitude of deceleration and acceleration in Pune 2 is just as high on average as in light city traffic (Pune 1) with the extreme events matching heavy city traffic (Pune 3). The highway portion of the MIDC, by contrast, shows relatively gentle acceleration and braking throughout.

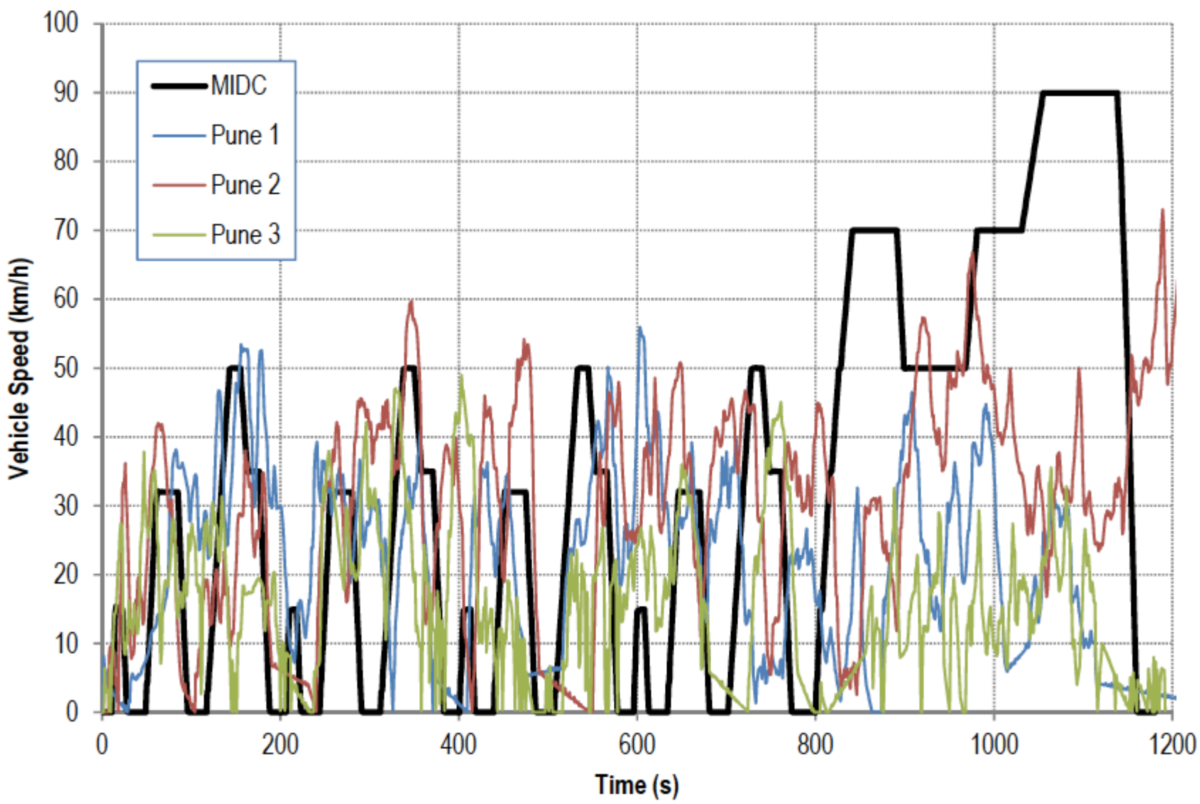
We expected these dramatic differences between the real-world driving profiles and the MIDC to translate into significant differences in vehicle performance, which is what we see in the Autonomie results

TABLE 6.18: CHARACTERISTICS OF ALL 3 PUNE DRIVING PROFILES AND THE MIDC

	Units	Pune 1	Pune 2	Pune 3	MIDC
Max acceleration	m/s2	3.68	3.39	5	1.06
Mean acceleration	m/s2	0.23	0.26	0.43	0.16
Max deceleration	m/s2	-2.15	-5.28	-6.19	-1.39

Cycle distance	miles	6	35.91	3.25	6.58
Driving Time	min	27.00	60.88	19.87	19.67
Maximum speed	mph	34.70	79.56	29.94	55.92
Mean speed	mph	12.12	36.24	11.65	26.70
Stop frequency	stops/mi	1.33	0.42	15.70	1.98

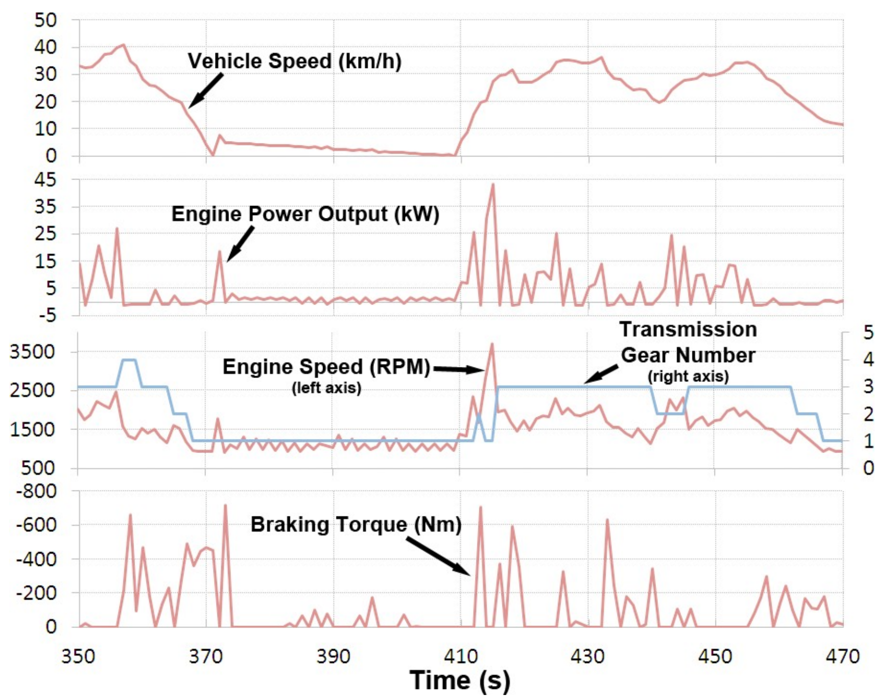
FIGURE 6.20: SPEED-TIME PLOT OF ALL 3 PUNE DRIVING PROFILES AND THE MIDC FOR THE FIRST 1200 SECONDS OF EACH CYCLE. THE PUNE CYCLES SHOW FAR MORE FREQUENT SPEED VARIATION AND SHARPER ACCELERATION EVENTS THAN THE MIDC. THIS VARIATION REFLECTS DRIVER EXPERIENCE IN THE BUSY STREETS OF MAJOR INDIAN CITIES.



6C.3: AUTONOMIE SIMULATION RESULTS

For each drive cycle, we modeled fuel use for the Swift-like compact car. Autonomie also allows calculations of GHG emissions per mile and power flow through individual vehicle components at any time instance during the simulation. Additionally, for detailed insight into the vehicle performance data that can be extracted from Autonomie, a 2-minute sample of the Pune 1 driving profile is shown in FIGURE 3, including vehicle speed, engine power output, engine speed, transmission gear state, and braking torque. By comparing the five plots within FIGURE 3, it is clear that engine operating characteristics, transmission shifting, and braking torque resemble what would actually occur in a vehicle. For instance, engine power and engine speed lie within reasonable levels, and peaks in these two quantities occur at time instances where rapid acceleration is requested. Engine speeds exhibit step increases or decreases based on transmission shifting events, and the time occurrence of the gear shifting is in line with requested vehicle speed. Finally, peaks in braking torque correspond with vehicle deceleration events, and the peaks in braking torque and engine power output never occur simultaneously. FIGURE 3 leads you to expect the Pune cycles to be fuel intensive: frequent and intense braking and re- acceleration ("start-stop driving") leads to more engine speed variance and engine power output per mile.

FIGURE 6.21: TWO-MINUTE SNAPSHOT OF KEY VEHICLE PARAMETERS FOR THE PUNE 1 DRIVING PROFILE.



The vehicle performance results for each driving profile are shown in TABLE 3. The MIDC overestimates fuel economy by approximately 35% relative to the average of the three Pune profiles. When compared to the heavy city traffic driving profile (Pune 3), the MIDC underestimates fuel use by over 50%. Such substantial deviations make a strong case for much deeper investigation of the magnitude of the errors introduced by the current fuel economy test procedure. If our findings hold true, we can conclude it is imperative that India revise the driving cycle it currently uses for emissions and fuel economy testing.

TABLE 6.19: COMPACT CAR PERFORMANCE IN AUTONOMIE. THE MIDC OVERESTIMATES REAL WORLD FUEL ECONOMY BY 35%

		Pune 1	Pune 2	Pune 3	MIDC
Distance Traveled	miles	5.23	35.76	3.21	6.57
Fuel Economy	mi/gal	29.27	28.86	22	41.91

Fuel Consumption	L/100 km	8.04	8.15	10.69	5.61
CO2 emissions	g/mile	308.88	313.27	410.88	215.72
Engine efficiency	%	28.53	31.64	29.61	29.88

6D: CONCLUSION AND POLICY IMPLICATIONS

This paper concludes that smart phones, using commercial apps, are capable of collecting data accurate and detailed enough to support significant advances in measuring, describing, and building models based on driving behavior and vehicle performance in India. We also demonstrate that we can get better data at a lower cost.

We found that a small sample of driving behavior in Pune, a city representative of many of the miles driven in India today and in the future, indicates that the use of the MIDC to rate car fuel economy could grossly overestimate the real-world fuel economy of the same car by 35% or more. At the individual level, inaccurate labels will mean that Indian car buyers cannot accurately plan a budget for the use and maintenance of a new car. At a societal level, the implications of these errors could be serious. Researchers usually assume that a vehicle's rated fuel economy is a good approximation of its real-world performance since the US and European ratings have been extensively refined to reflect this. Our findings imply that in the case of India a similar assumption could result in large-scale under-estimates in projections of oil demand, greenhouse gases and air pollution. This, in turn, could lead to inadequate policy, research and planning actions to solve the problems that bedevil Indian transport.

Other implications of our findings are:

- Better data collection about real driving behavior, if applied in regulation, can minimize discrepancies between rated and actual fuel economy and support policy development based on more realistic understanding of fuel use.
- Such data collection can be done at a very small fraction of the traditional approach's cost, leveraging India's great cellular telephone leapfrog.
- Furthermore, as India develops, driving behaviors may change. Ongoing measurement of behavior can enable an evolving national set of drive cycles for regulatory purposes.

Vehicle technologies that perform well at highly variable speeds (aka "start stop driving") will be especially beneficial in Indian cities, compared to Western cities (assuming the European cycle is a reasonable representation of driving in these locations). Such vehicles include conventional cars with larger starter motors, hybrid-electric, plug-in hybrid-electric, and pure- electric vehicles. Our group in undertaking research to quantify the benefits of these advanced drivetrains in India.

The ease with which we were able to collect this data also has implications for other GHG and petroleum concerns related to transportation behavior. For example, understanding how new vehicle technologies will interact with Indian driving conditions can leverage similar smart phone-type data (Gonder, Markel, Thornton, & Simpson, 2007). Going further, this research can take advantage of the proliferation of off-the-shelf devices that plug into a vehicle's On-Board Diagnostic (OBDII) port, and send data from the vehicle's on-board computer to the smart phone via Bluetooth. The smart phone then marries engine data (such as air intake, pedal position, temperature, etc) to time stamps and locations, enhancing understanding of the vehicle's reaction to the driving conditions. Such devices are available at many commercial websites for less than $25.

India can use its phone fleet as speed probes to leapfrog in-road sensors for real-time traffic monitoring. Furthermore, Indians can use smart navigations apps on their phones that not only direct users to their destination in a timely, but also coordinate the advice given to calm traffic. India could also leapfrog the reliance on complex and often inaccurate transportation demand modeling based on origin/destination tables and extensive household travel surveys. By using directly measured data that does not fall victim to the failures of human memory like many surveys, and automatically tags trips by purpose, demographics, origin/destination, and more, Indian municipal policy makers and urban planners can accomplish more sophisticated planning at lower cost, leapfrogging Western transportation policy (Stopher & Greaves, 2007).

These examples are constrained to transportation that reduces GHGs. Dozens more examples exist in this vein, as well as potential applications for research, policy making, and policy implementation leveraging smart phones for automotive crash reduction, drunk driver detection, freight optimization, and more. And while India is especially able to take advantage of smart phones because of its mobile phone leapfrog, other developing nations will find many of the same benefits.

CHAPTER 6: ACKNOWLEDGEMENTS

This work was supported by the Regulatory Assistance Project through the U.S. Department of Energy under Contract No. DE-AC02-05CH11231. The authors would like to thank Ranjit Deshmukh for assistance in data collection. The authors also thank the National Science Foundation Graduate Research Fellowship and StreetLight Data.

7: DENSITY AND VMT

CHAPTER 7: PREFACE

This chapter uses more modern data collection techniques, described in Chapter 2, to explore an important point raised in Chapter 3 – VMT is no longer dominated by the commute. Thus, how can we work towards VMT reduction when the rise in VMT is in non-commute related activities, whereas many of our traditional planning frameworks and tools focus on reducing the commute?

CHAPTER 7: ABSTRACT

Vehicle-miles travelled (VMT) is the dominant lever of these greenhouse gas-emissions as well as the criteria air pollutants, and negative health impacts associated with America's dependence on trucks and cars. After a brief dip in the recession, total US personal VMT is on the rise again, as is per capita VMT, as is truck-based freight VMT (Federal Highway Administration, 2017).

An ongoing debate continues in the literature – what is the precise impact of "density" on VMT? As commute VMT is now only ~28% of total in the US (Federal Highway Administration, 2017), it has become more important to ask: What is the impact of density on non-commute VMT? Even if these questions had been definitively answered in the past (which they haven't) modern trends like the rise of eCommerce and telecommuting, plus the spike in housing prices in many urban centers, demand new and updated study of these questions. Answering such complex questions with traditional data tools like surveys has been shown to be highly limited.

In this study I use data collected from millions of smartphones—in conjunction with density data, demographic data, and data derived from traditional surveys—to measure the daily VMT of 129,000 workers and residents across the Austin-Bergstrom, TX metropolitan area. The approach enables a very granular analysis of the relationships between demographics, density factors and total VMT, as well as VMT for different trip purposes.

I use two statistical approaches to describe the relationships. First, I organize residents of the region into 30 clusters defined by the pairing of the density of their homeplace and the density of their workplace (or their lack of fixed workplace). For each cluster I measure the mean and standard deviation of daily VMT. Next, I measure the correlation between different types of density and different types of VMT. I find that:

- The combination of work and home location density together yield more insight into total VMT than either work or home density alone. *This confirms the importance of integrated policy for VMT reduction, not simply promoting residential density.*
- People who live in a low-density area have the longest average daily VMT, no matter how dense a place they work in. For example, a resident of a low-density block group will drive about many miles per day whether they work in the most dense part of downtown or another low-density environment. *This has implications for cities that have invested in dense urban employment centers – but where housing pricing may be driving the workers of those centers to live further out of town.*
- For people who work from home/do not work, and for people who do not work at a fixed place, the residential density still strongly impacts daily VMT. Non-commute VMT is also a larger predictor of total VMT than commute lengths. *Together this reinforces the importance of non-commute driving.*
- Individuals without a fixed workplace have a higher VMT per day than their commuting or work from home neighbors. This could be a natural consequence of the fact that many of these individuals are professional drivers. *This result also deserves further exploration in future work, as increasing "gig" work and other non-traditional schedules could have consequences for VMT and should be measured carefully*

7.A INTRODUCTION AND MOTIVATION

Vehicle-miles travelled is the dominant lever of these greenhouse gas-emissions as well as the criteria air pollutants, and negative health impacts associated with America's dependence on trucks and cars. After a brief dip in the recession, total US personal VMT is on the rise again, as is per capita VMT, as is truck-based freight VMT (Federal Highway Administration., 2017).

Much of the data collection, research policy, urban/transit design aimed at understanding and reducing VMT over the past 50 years has focused on the commute. However, in the past decades a growing body of literature has pointed out that this focus may have led us down a suboptimal path, or at least may no longer be effective, as discussed below.

An ongoing debate continues in the literature – what is the precise impact of "density" on VMT? As commute VMT is now only ~28% of total in the US (Federal Highway Administration, 2017), it has also become more important to ask: What is the impact of density on non-commute VMT? Even if these questions had been definitively answered in the past (which they haven't) modern trends like the rise of eCommerce and telecommuting, plus the spike in housing prices in many urban centers, demand new and updated study of these questions. Answering such complex questions with traditional data tools like surveys has been shown to be highly limited, as discussed below.

In this study I use data collected from millions of smartphones—in conjunction with density data, demographic data, and data derived from traditional surveys—to measure the daily VMT of workers and residents in every blockgroup of the Austin-Bergstrom, TX metropolitan area ("Austin area"). This builds on a growing trend, in the academic literature and practice, of smartphone-derived metrics for transportation behavioral analyses of a full region. The scope of this "big data" enables a very granular analysis of the relationships between demographic and density factors and total VMT, as well as VMT for different trip purposes. As found by Gately et al in 2015, used of aggregate data has led to errors in local transportation VMT calculations, and thus GHG impact calculations, through false downscaling (Gately, Hutyra, & Wing, 2015). My work builds on Gately and related findings by adding even more spatial precision and richness than they considered, taking advantage of smartphone-derived data.

I hypothesize that a simple measure of density cannot explain VMT alone. We need a more integrative lens on density alongside other important factors – for example, comparing residential and workplace density, the type of work done by an individual, income, and more – to understand VMT in a way that can be used powerfully by policy makers and planners. The observation that an integrated approach to transportation is required has been brought up by many scholars before (e.g. Schipper & Marie-Lilliu, 1999) and was called out in the most recent Intergovernmental Panel on Climate Change reports on transportation (Sims et al., 2014).

However, a large gap exists between saying that transportation planning must be "integrative" and actually deploying concrete, locally impactful "integrative" measures and policies. By using advanced data provided by the ubiquity of mobile devices, I am able to add far more quantitative and granular support and insight to this argument thus taking one step towards closing that gap.

To test this hypothesis, I use two statistical approaches to describe the relationship between VMT, density and other factors. First, I organize residents of the region into 30 clusters defined by the pairing of the density of their homeplace by quintiles and the density of their workplace by quintiles (or their lack of fixed workplace). For each cluster I measure the mean and standard deviation of daily VMT. This approach allows an intuitive way to show the importance the pairing of densities, in other words, a more integrative look at the relationship between multiple types of density and daily

VMT. Next, I analyzed the various factors' correlation linearly, in a multivariate regression. The key findings are:

- The combination of work and home location density together yield more insight into total VMT than either work or home density alone. *This confirms the importance of integrated policy for VMT reduction, not simply promoting residential density.*
- People who live in a low-density quintile have the longest average daily VMT, no matter how dense a place they work in. For example, a resident of a low-density block group will drive about many miles per day whether they work in the most dense part of downtown or another low-density environment. *This has implications for cities that have invested in dense urban employment centers – but where housing pricing may be driving the workers of those centers to live further out of town.*
- No matter how dense a place someone works, the more dense their home block, the fewer average VMT they will drive. These savings become sharper higher on the density curve, suggesting compounding benefits of living in a high-density environment. *This compounding benefit may be a result of reduced VMT for non-commute trip purposes, such as shopping and entertainment.*
- Without also having high-density workplaces, the benefits of increased residential density flatten the between the 2nd and 3rd quintile. At first glance, this confirms Gately's finding that after 1650 residents / km^2 the benefits of more density may flatten. However, when paired with insight into the workplace density, and for people with no fixed workplace, this "flattening" disappears and going from 1300 to 2100 residents/km^2 or more yields additional significant VMT savings. *Thus, ultimately, this work challenges this finding of Gately – instead finding that, at least in Austin, pushing VMT extremely high yields further benefit when done in conjunction with workplace density.*
- For people who work from home/do not work, and for people who do not work at a fixed place, the residential density still strongly impacts daily VMT. Again, this highlights the importance of non-commute driving.
- Individuals without a fixed workplace have a higher VMT per day than their commuting or work from home neighbors. This could be a natural consequence of the fact that many of these individuals are professional drivers (Uber, delivery, long haul truck) or drive between gigs (Plumbers, gardeners). *This result also deserves further exploration in future work, as increasing "gig" work and other non-traditional schedules could have consequences for VMT and should be measured carefully*

This builds on a body of literature that complexifies the notion that more residential density leads to less driving. By amplifying the sample size and granularity of data with the passive smartphone data collection technique, it confirms to some literature based on surveys or behavioral modelling, and challenges others. The relations described in this paper can be used to improve such behavioral forecasting models, and the broader policy conversation. I conclude that locally-specific granularity is important when developing metrics that are meant to influence corporate, individual, or government decisions around location choice, infrastructure, and incentives. Examples of such applications include LEED certification for workplaces and residences, VMT-target based policies such as California's SB 743. Without spatial granularity, the wrong investments may be rewarded or punished. This paper demonstrates that measurement at such granularity is feasible, accurate, and supported by prior work.

7.B LITERATURE REVIEW

Traditionally, increase in density and decreasing the distance between jobs and residences have been the default approach towards both decreasing VMT and increasing jobs accessibility. However, as discussed in the literature review below, other academic work challenges this assumption. Key to the unresolved nature of this debate is a lack of adequate data, as discussed below. As stated in Cervero and Murakami 2010: "Doubts about the potential GHG-reducing effects of sustainable urbanism are understandable in light of inconsistent research findings to date" (Cervero & Murakami, 2010).

Developing a deeper and more accurate understanding between land use and density with VMT reduction is critical. Policy makers prefer simpler, more "certain" calculations of impact for policies. Thus, because this behavioral relationship appears uncertain, policy makers tend to focus solely on simpler, technical solutions for reducing transportation's GHG impact, like electric vehicles. This is dangerous, as technical solutions alone are necessary but not sufficient to achieve transportation GHG reduction targets (Frank, Kavage, & Appleyard, 2007) (Cervero & Murakami, 2010).

Several excellent papers, cited below, have covered the literature of this debate in detail. Thus, I will provide a relatively brief summary.

7.B.1 SUPPORT FOR THE CORRELATION OF DENSITY, SHORTER COMMUTES, AND REDUCED TOTAL VMT

Those who argue that increased density leads to decreased commute VMT, and thus decreased total VMT often come from a "top down" perspective, citing theory or data about broad, regional trends.

As summarized by Cervero and Murakami in 2010, a pair of recent impactful publications by Ewing found that denser development could cut US and California VMT, respectively by 30% (Ewing, 2008). Other literature reviews in 2008 also centered on a range of VMT reduction potential of 10-30% (e.g. (Cervero & Murakami, 2010)(Eakin & Goldstein, 2008)) when density is combined with transit and other policies such as congestion pricing.

Several others have used data from large regional datasets and surveys to test this theory. For example, Cervero and Murakami studied the relationship between urban density and VMT per capita in 370 regions using structural equation modeling in 2010. Ultimately, they conclude that a doubling of population density (a nearly impossible near-term bar) yields a 38% reduction in VMT.

Many recent papers agree that residential density should not be the sole focus in reducing VMT. They claim that residential density *alone* is not predictive or causative of reduced VMT – it requires integration with demographics, transit options and other infrastructure investments. This more wholistic approach is sometimes referred to as "accessibility" or the "4Ds of density." In addition, some studies point out that the density of destinations (like work) are as important as residential densities. (Bhat & Guo, 2007), (Cervero, 2002), (Iacono, Krizek, & El-Geneidy, 2010), (Leslie et al., 2007) , (Cervero & Murakami, 2010), (Duncan, Aldstadt, Whalen, Melly, & Gortmaker, 2011) (Singh et al., 2018)).

This support for residential density in conjunction with other tools like workplace density or transit has had many implications for policies designed to reduce VMT and thus GHGs.

7.B.2 CHALLENGING THE RELATIONSHIP OF DENSITY, COMMUTE AND REDUCED VMT

Those who argued that increased density and decreased commute VMT are not necessarily correlated usually cite research that derives from a bottom up perspective, or criticize prior work for self-selection bias. The challenges fall into several categories of arguments, as summarized below:

1) **Model bias and self-selection bias –** Some of these papers, such as (Singh et al., 2018), argue that the relationship found between urban density and reduced VMT is in part a result of self-selection. People who value not driving self-select to live in denser environments. Thus, denser neighborhoods will usually have lower daily VMT up until the point where the affordable, dense-living supply for this type of person is saturated. This is captured as endogeneity bias in a broader meta review by Bhat and Guo (Bhat & Guo, 2007).
2) **There's a density "threshold" that impacts VMT, but it's not linear.** Gately et al found that transportation emissions reduce with increased population density up to 1650 people/km^2, but then the relation largely flattens (Gately et al., 2015).
3) **Reducing one kind of VMT with density adds to another kind of VMT for the household.** For example, one study in Austin found that residents in a dense new urbanist environment became bored with local restaurant/shopping options (and were drawn to a new Wholefoods across town), thus actually increasing their average VMT compared to control residents in less dense neighborhood (Handy & Clifton, 2001). At much larger scale (370 MSAs across the US), Cervero and Murakami found that increased density, while it does reduce auto-commute share, leads to indirect VMT increases mainly due to pathways associated with more road building, and more retail activity. This offset some (not all) of the overall VMT decrease from density.
4) **Reducing one kind of VMT adds another for the region.** Others have found that dense, vibrant cities, while reducing transportation in the immediate vicinity, increase greenhouse gas emissions in the overall metropolitan area (Jones & Kammen, 2014). (Kockelman, 1997) (Mindali, Raveh, & Salomon, 2004) (Chatman, 2003)). Jones and Kammen propose that this is especially true with density leads to a vibrant downtown, with increasing housing prices which over time make super-commutes into town the only affordable option for many workers (Jones & Kammen, 2014).
5) **Aggregation of data has led to miscalculation of the relationship between density and VMT/GHG.** Chatman point out the applications of the NHTS and NPTS surveys' lack of spatial data made them infeasible to use *below* the highly aggregate MSA level, and thus to understand the impact of local density, accessibility, transit proximity, etc. (Chatman, 2003). In a large review in PNAS in 2015, Gately et al found that a lack of spatial precision in previous studies (including many of those cited above) led to errors in downscaling from the aggregate to the specific region. This lead to flawed impact forecasts for particular policies, developments, and other decisions (Gately et al., 2015). Gately's review concluded that: "high-resolution estimates…are critical both for accurately quantifying surface carbon fluxes and for verifying the effectiveness of emissions mitigation efforts at urban scales… Geographic differences in the density–emissions relationship suggest that smart growth" policies to increase urban residential densities will have significantly different effects on emissions depending on local conditions, and may be most effective at low densities."

7.B.3 GAPS IN RESEARCH

As pointed out by many of the studies above, several gaps in data are in part to blame for the lack of resolution on the question of VMT and density. The most important data gaps are:

1. **Scalability of case studies and longitudinal studies:** Several papers that go in-depth into complexities of VMT associated with one newly density neighborhood or building are limited in applicability because of the small sample of locations ((Handy & Clifton, 2001), (Popovich & Handy, 2015). *My work mitigates this in part by using big data to scan all parts of a large metro area.*
2. **Lack of granular, accurate baseline VMT Data:** Because of his source of vehicle volume data (the Highway Performance Monitoring System, or HPMS) even Gately pointed out that his approach was hampered by lack of accuracy, and limiting visibility to only federally funded roads. Cervero used the same source to calculate VMT in his work and remarked on its fundamental limitations (Cervero & Murakami, 2010). The HPMS source contains no information on trip purpose or demographics of drivers. *My work mitigates this by looking at all VMT travelled on all road types and differentiating this by purpose and driver income as well as home and work place.*
3. **Few updates in light of major shifts in transportation behavior. Most of the studies of density and VMT** Most of the comprehensive studies were done on data collected before the Great Recession and before massive shifts in transportation took off in the US including: the rise in urban housing prices, the dominance of eCommerce, the advent of ride hailing and increase in non-traditional commutes (such as telecommuting, and gig work). *My work mitigates this by looking at data from 2019.*
4. **Looking at VMT at the locality-level, not by the household or individual** The major region-wide recent studies by Gately and Cervero estimated VMT by neighborhood or MSA. For example – Neighborhood X has a total VMT of Y. However, this eliminates and important behavioral linkage – many people drive in regions that are not near their home or work. A resident certainly contributes to VMT near their homeplace, but also in the neighborhoods between home and work and daycare and shopping and recreational activities. Gately and Cervero could not, because of the limitations of their road-segment based VMT data, look at the relationship of density of home and work neighborhood to total personal VMT. Understanding this linkage is critical to effectively guide policy. Household survey-based studies could use this linkage, but were limited by extremely small sample sizes. *My work mitigates this gap by having the mass-scale of Gately and Cervero, married with the ability to look at personal VMT in relation to home and workplace density from studies like Handy.*

7.B.4 USE OF CELL AND SMARTPHONE-BASED DATA IN TRANSPORTATION DEMAND MEASUREMENT

Most of the papers above used household travel surveys or the HPMS as the input data for VMT. These surveys, -scale household efforts or smaller building occupant surveys have well-documented shortcomings. Oft-cited problems include burdensomeness to participants, (Hartgen, 2009), high cost (Stopher & Greaves, 2007), low response rates (Wilson, 2004), fallibility of memory in the subjects (Stopher & Greaves, 2007) (Bohte & Maat, 2009) including over-emphasis of work-based travel in human memory (Hu, 2004).

The transition from surveys to mobile device-derived data discussed in this paper reflects work done in the broader travel survey community to use massive data derived from mobile smartphone and GPS devices, passively collected. (e.g. (McGowen & McNally, 2007), (Zhang, Qin, Dong, & Ran,

2010) (Harrison, 2012) (Milam, Stanek, & Jackson, 2012) (McCahill, n.d.), (Turner & Koeneman, 2017), (Sheppard et al., 2019) (Monz, Mitrovich, D'Antonio, & Sisneros-Kidd, 2019)).

Collectively, these studies have found many benefits to this approach have been sited including: reduced costs, improved sample size and distribution, improved spatial granularity and precision leading to integration of richer data about destinations, routes, mode, land use, demographics, and other factors. Accuracy has been confirmed by comparison to local surveys (Batran, Mejia, Kanasugi, Sekimoto, & Shibasaki, 2018), models, and sensor data collection (Kissinger & Reznik, 2019).

Many of the earliest studies using this data relied on data collected from cellular towers. This data has low spatial precision (in the realm of several hundred meters, with variation). This was oft-cited as a flaw and block to deeper use of this data for transportation behavioral analysis (e.g. (Wang, Schrock, Vander Broek, & Mulinazzi, 2013)). This paper uses the next generation of data, using the location-based services technology within smart phones and GPS-derived data to access far more spatially precise locational data (StreetLight Data, 2019). In the past two years, these has become the preferred sources in academic and planning circles due to its improved precision (Monz et al., 2019) (Lee & Sener, 2017).

Even more recently, this granularity afforded by new data sources has been used to challenge results from traditional surveys. For example, Kissinger and Reznik used similar methods to this paper to both update and spatially place the greenhouse gas emissions from commuting within Tel-Aviv (Kissinger & Reznik, 2019). Monz *et al* used this data to measure travel patterns for park visitation, finding the approach reduced cost and allowed for measurements of more granular, diffuse geographies (Monz et al., 2019).

7.C DATA AND METHODS

In this study, I used data derived from Mobile Devices in conjunction with more traditional data sources like the most recent data available from the American Community Survey (ACS), US Census, the EPA's Smart Location Database (SLD), and the National Household Travel Survey (NHTS). I indexed all available data to the Census Bloc or Tract level as indicated by the specific results discussions below.

7.C.1 DATA SOURCES

Table 1 shows the variables considered in this paper, and their source.

TABLE 7.20: DIFFERENT TYPES OF DATA USED, AND THEIR SOURCES

Input Data	***Unit***	***Source***
Residential adult population	People	ACS
Number residential mobile devices	Devices	StreetLight Data
Number worker mobile devices	Devices	StreetLight Data
Residential density	Residents / km^2	ACS
Employment density	Index 0-1	Smart Location Database
Commerce density	Index 0-1	Smart Location Database
Total daily VMT / resident devices	Average and standard deviation in miles	StreetLight Data
Total daily VMT / worker devices	Average and standard deviation in miles	StreetLight Data
Total daily VMT / visitor device	Average and standard deviation in miles	StreetLight Data
Commute VMT / resident	Average and standard deviation in miles	StreetLight Data

Commute VMT / worker	Average and standard deviation in miles	StreetLight Data
Commute VMT / visitor	Average and standard deviation in miles	StreetLight Data
Non-commute VMT / resident	Average and standard deviation in miles	StreetLight Data
Non-commute VMT / worker	Average and standard deviation in miles	StreetLight Data
Non-commute VMT / visitor	Average and standard deviation in miles	StreetLight Data
Total Tract VMT	Miles	StreetLight Data

7.C.2. MOBILE DATA SAMPLE

The dataset from StreetLight Data covered travel from April 2019. In the Austin-Bergstrom MSA this sample was 129,967 devices (13.5% of the MSA's population). Only trips from days where all or most of the travel day appeared to be collected were used, totaling 3.0M travel days, and 9.4M trips.

Of these devices, 56,004 had an identifiable "home" place (defined as the block with residential zoning on which the device spent more than 7 nights) as well as a distinct identifiable "work" place (defined as the block where the device spends more than 7 days per month). We note that this workplace also could cover college students going to one of the several universities in the area. 46,678 devices have the same "home" and "work" place. This includes people such as retirees, stay-at-home parents, people working from a home office, and some university students who live on campus. 24,728 have a clear home place, but no constant workplace. These can include people whose job is in a different location each day (e.g. plumbers, electrical linemen, people with multiple part time jobs). A very small number had no identifiable work or homeplace and these were eliminated from the study.

TABLE 7.21: SAMPLE SIZE AND CHARACTERISTICS FROM MOBILE DEVICE DATA

Work-from-home case	**Number Devices**	**Number Complete Travel Days**	**Total Trips**	**Avg Trips per Travel Day per Device**
Work from a block distinct from home block	56,004	1,334,782	4,122,330	3.1
Same home and work block	46,678	1,048,612	3,320,212	3.2
No constant work block	24,728	594,091	1,795,602	3.0
No home or work identified	2,557	58,857	178,862	3.0
SUM	129,967	3,036,342	9,417,006	

This sample size for one month in Austin is approximately the same for the full national sample size for the 2017 NHTS (Federal Highway Administration., 2017). To understand the representativeness of the smart phone sample, I compared certain aggregates from the smart phone data to results taken from the NHTS's subsample for the Austin-Roundrock CBSA, which is largely coincident with the Austin-Bergstrom MSA. As shown in Table 3, below, in general the smartphone-based data are slightly lower than what was found in the NHTS sample (with the exception of the other-based trip length, which is higher).

TABLE 7.22: COMPARISON OF AGGREGATE TRAVEL MEASUREMENTS FROM SMART PHONE SOURCE AND NHTS.

Comparisons	Veh. Trips / Day / Person	Miles / Veh. Trip	VMT / Day / Person	Home Based Avg Length	Work Based Average Length	Other Based Average Length
NHTS	3.4	10.9	37.8	12.5	13.8	8.9
Smartphone April 2019	3.1	10.3	30.9	10.3	9.7	10.4
Delta (% to NHTS)	-11%	-6%	-18%	-18%	-30%	+17%

Neither source can be considered true "ground truth" as both are sampled and then expanded. However, the smart phones may turn data collection off, or run out of battery, throughout the day. It's likely that some days the devices do not capture the every single full travel day (StreetLight Data, 2019). Since I am comparing VMT measured by the phones to other VMT measured by phones, I chose assume that any missed data from the smart phones is missed in an evenly distributed way. Thus, no additional expansion of this data (which would introduce further, more opaque assumptions) was performed

7.D EMPIRICAL RESULTS

I hypothesize that, historically it may have been true at a very broad level that more density is correlated with less daily VMT. But the opposite is often true at in particular areas. I explore this hypothesis with a granular study of work-related and non-work VMT distances for residents, workers, and visitors in all blockgroups in Austin. I structure the broad enquiry into four questions:

- Is commute distance positively or negatively associated with an individual's total VMT?
- Is residential density, workplace density, and the pairing positively or negatively associated with an individual's total VMT?
- Is "other" destination density positively or negatively correlated with total and non-work VMT?
- What is the relation between the prior trends?

To answer them, I break the population into 30 groups, as shown in the following table. First, I organized all the blockgroups in the Austin-Bergstrom MSA into quintiles first by residential population density (residents per square kilometer) and by job density as defined by the Smart Location database. Then, I assigned each individual mobile device in the database to one of the pairs. For example, a device which lived in a blockgroup classified as "Quintile 1" for residents and working in a blockgroup classified as "Quintile 2" for workplaces would fall in Row 1, Column 2, etc.

7.D.1. RELATIONSHIP OF HOME- AND WORK-PLACE DENSITIES TO TOTAL DAILY VMT

First, I analyzed all the combinations by a unit of average total daily VMT. Tables 4 and 5 show the results by homeplace and workplace density.

TABLE 7.23: RELATIONSHIP OF RESIDENTIAL BLOCKGROUP DENSITY QUINTILE ON VMT OF RESIDENTS

Residential blockgroup density percentile	Mean	25th percentile	75th percentile
Q1: 0 to 169 res/km2	36.0	18.9	46.7
Q2: 169 to 760 res/km2	31.1	16.3	39.9
Q3: 760 to 1375 res/km2	28.0	14.1	35.7
Q4: 1375 to 2176 res/km2	26.3	13.0	33.6
Q5: 2176 to 9000 res/km2	24.6	11.8	31.4
% Increase from Moving from Least to Most Dense Quintile	46%	60%	48%

Daily VMT as the mean and as 25th and 75th percentiles go down significantly moving from the most to least dense quintile of blockgroup. As discussed later, much of the variance between the percentiles is explained by pairing an individual's home and work-place densities.

TABLE 7.24: RELATIONSHIP OF WORKPLACE BLOCKGROUP DENSITY QUINTILE ON VMT OF RESIDENTS.

Workplace blockgroup density percentile (for people who commute or work from home/don't work)	Mean	25th percentile	75th percentile
Q1: 0 to 0.05 job density (SLD)	34.8	17.8	44.7
Q2: 0.05 to 0.23 job density (SLD)	31.5	16.1	40.3
Q3: 0.23 to 0.81 job density (SLD)	30.2	15.1	38.8
Q4: 0.81 to 2.68 job density (SLD)	28.4	13.9	36.7
Q5: 2.68 to 4 job density (SLD)	27.9	13.5	36.4
No fixed workplace	32.4	15.4	41.7
% Increase from Moving from Least to Most Dense Quintile	25%	32%	23%

The impact of workplace density on an individuals' daily VMT is also clear, but of lower magnitude. It appears also appears to flatten between the 3rd and 4th quintile of blockgroup. Note that all workers in the first five rows include traditional commuters and people who work from home/don't work. Row six shows the average VMT from people who have unfixed workplaces, such as plumbers, Uber or other commercial drivers, etc.

Table 6 presents the full 30 clusters, in which we look at the impact of both workplace and residential density on an individual's VMT. How to read this chart: Someone who lives in a lowest density residential blockgroup (Q1) and works in the highest density work blockgroup (Q5) drives an average of 36.88 miles per day. n = 118854 mobile devices.

TABLE 7.25: AVERAGE PERSONAL DAILY VMT BY HOME BLOCKGROUP DENSITY QUINTILE AND WORK BLOCKGROUP DENSITY QUINTILE. THIS TABLE INCLUDES ALL AREA RESIDENTS WHETHER OR NOT THEY WORK FROM HOME.

Workplace job density → Homeplace res. density ↓	Q1: 0 to 0.05 job density (SLD)	Q2: 0.05 to 0.23 job density (SLD)	Q3: 0.23 to 0.81 job density (SLD)	Q4: 0.81 to 2.68 job density (SLD)	Q5: 2.68 to 4 job density (SLD)	% increase from moving from least to most dense quintile	No fixed work
Q1: 0 to 169 res/km2	36.05	34.29	34.11	31.45	36.88	-2.3%	39.73

Q2: 169 to 760 res/km2	31.52	31.47	30.18	29.61	30.05	4.9%	36.81
Q3: 760 to 1375 res/km2	30.64	28.46	28.63	26.60	26.13	17.3%	32.68
Q4: 1375 to 2176 res/km2	30.58	28.00	27.04	25.14	24.43	25.2%	30.56
Q5: 2176 to 9000 res/km2	29.73	27.15	26.11	24.17	22.54	31.9%	31.05
% increase from moving from least to most dense quintile	21%	26%	31%	30%	64%	60%	28%

Table 6 yields several important findings:

- The combination of work and home location density together yield more insight into total VMT than either work or home density alone. *This confirms the importance of integrated policy for VMT reduction, not simply promoting residential density.*
- People who live in a low-density quintile (Residential Quintiles 1 and 2) have the longest average daily VMT, no matter how dense a place they work in. For example, a resident of a low-density block group will drive about many miles per day whether they work in the most dense part of downtown or another low-density environment. *This has implications for cities that have invested in dense urban employment centers – but where housing pricing may be driving the workers of those centers to live further out of town.*
- No matter how dense a place someone works, the more dense their home block, the fewer average VMT they will drive. These savings become sharper higher on the density curve, suggesting compounding benefits of living in a high-density environment. In other words, even if you work in a far-flung suburban office park, moving from a 3rd to 4th quintile home block group yields lower VMT…and moving from the 4th to 5th quintile home block group yields even more savings. *This compounding benefit may be a result of reduced VMT for non-commute trip purposes, such as shopping and entertainment.*
- Without also having high-density workplaces, the benefits of increased residential density flatten the between the 2nd and 3rd quintile. This largely confirms Gately's finding that after 1650 residents / km^2 the benefits of more density may flatten. However, when paired with insight into the workplace density, and for peope with no fixed workplace, this "flattening" disappears and going from 1300 to 2100 residents/km^2 or more yields additional significant VMT savings. *Thus, ultimately, this work challenges this finding of Gately – instead finding that, at least in Austin, pushing VMT extremely high yields further benefit when done in conjunction with workplace density.*
- The home blockgroup density also matters even for people without a fixed workplace again highlighting the importance of non-commute driving. These individuals have a higher VMT per day than their commuting or work from home neighbors. This could be a natural consequence of the fact that many of these individuals are professional drivers (Uber, delivery, long haul truck) or drive between gigs (Plumbers, gardeners). *This result also deserves further exploration in future work, as increasing "gig" work and other non-traditional schedules could have consequences for VMT and should be measured carefully*

Nota bene – using road density as the quintile input for home and workplace density yielded very similar results. Thus, this alternative measure may be used if data about resident or job density is unavailable or dated in the future.

TABLE 7.26: DISTRIBUTION OF SAMPLE (AS NUMBER OF MOBILE DEVICES ANALYZED) FOR EACH BLOCKGROUP QUINTILE PAIR. TOTAL NUMBER OF DEVICES = 118,854.

Workplace job density → Homeplace res. density ↓	Q1	Q2	Q3	Q4	Q5	No fixed
Q1	8.2%	4.2%	2.3%	1.8%	1.9%	4.8%
Q2	3.4%	6.8%	6.2%	3.7%	4.1%	6.4%
Q3	1.3%	2.5%	3.6%	3.2%	3.4%	3.9%
Q4	0.7%	2.0%	2.2%	2.7%	3.4%	3.4%
Q5	0.5%	1.4%	2.1%	2.5%	4.4%	3.0%

Table 8 shows the standard deviation on the daily VMT per cluster, expressed as a percent of the mean.

TABLE 7.27: STANDARD DEVIATION, AS A PERCENT OF MEAN VMT BY CLUSTER. THE STANDARD DEVIATION INCREASES IN THE DENSER QUINTILES.

Workplace job density → Homeplace res. density ↓	Q1	Q2	Q3	Q4	Q5	No fixed
Q1	68%	67%	67%	69%	61%	72%
Q2	70%	70%	72%	70%	69%	72%
Q3	75%	73%	73%	72%	70%	81%
Q4	80%	74%	73%	77%	75%	75%
Q5	82%	86%	75%	76%	78%	85%

This shows that the variance is widespread, and increases as a percent of total in the higher density blocks. Deeper study of extreme drivers even in high-density neighborhoods is important for policy makers – as me must be ahead of any trends that make what used to be an outlier into the norm.

7.D.2 WORKING FROM HOME: WHAT IS THE IMPACT ON VMT?

For devices whose home (dominant nighttime) and "work" (dominant daytime) location are on the same census block, and thus can be said to "work from home," the importance of density of that block still holds, as shown in the Table 9:

TABLE 7.28: IMPACT OF DENSITY ON DAILY VMT FOR PEOPLE WHO STAY AT HOME DURING THE DAY. THE IMPACT OF DENSITY MATTERS EVEN WHEN THE NOTION OF A "COMMUTE" IS REMOVED. N = 46,678 DEVICES.

Home/work block density	Q1: 0 to 169 res/km^2	Q2: 169 to 760 res/km^2	Q3: 760 to 1375 res/km^2	Q4: 1375 to 2176 res/km^2	Q5: 2176 to 9000 res/km^2
Average Daily VMT	33.60	30.96	28.49	27.20	25.09

This result again highlights the importance of density to influence non-commute travel, as commutes do not occur for people who do not work or work from home.

As shown in Table 10, people who work from home or do not work travel nearly as many miles per day as those who commute, but only just 4-13% fewer. This finding indicates that people who work from home use some of the time saved by not driving to work to pursue other activities more than their commuting counterparts do, such as picking up children from school or activities, sports, or shopping. And, the denser a place they live in, the fewer such miles they drive.

The same trend holds true for people with unfixed workplaces. In both cases, the VMT decreases the denser the residential block.

TABLE 7.29: AVERAGE DAILY VMT BY RESIDENTIAL BLOCKGROUP DENSITY AS AN INDEX WHERE "TRADITIONAL" COMMUTERS = 1 (SHOWN IN ROW 1) AND UNFIXED WORKERS ARE IN ROW 2.

Home block density	Q1: 0 to 169 res/km^2	Q2: 169 to 760 res/km^2	Q3: 760 to 1375 res/km^2	Q4: 1375 to 2176 res/km^2	Q5: 2176 to 9000 res/km^2
Work and home in separate blocks	1.00	1.00	1.00	1.00	1.00
Work from home or do not work	0.93	0.96	0.97	0.96	0.87

7.D.3 INCOME AND TRIP PURPOSE DISTRIBUTION: WHAT'S THE IMPACT ON VMT?

In order to explore the relationships between income, trip purpose distribution and total VMT I moved from a cluster analysis to a multivariable linear regression approach, as the number of clusters would become unwieldy when mixing in new variables.

First, we look at several variables' correlation with average VMT per day and each other in a correlation matrix. In this matrix shown in Table 11, the stronger the positive correlation, the darker the green in the cell. The stronger the negative correlation, the darker the orange in the cell.

TABLE 7.30: CORRELATION MATRIX BETWEEN VMT AND OTHER CHARACTERISTICS. THE STRONGER THE POSITIVE CORRELATION, THE DARKER THE GREEN IN THE CELL. THE STRONGER THE NEGATIVE CORRELATION, THE DARKER THE ORANGE IN THE CELL. N = 128,372

	Avg VMT/ day	HBW trip length	HBO trip length	WBO trip length	OBO trip length	Mean residential household income	Residential density
HBW trip length	0.49						
HBO trip length	0.59	0.32					
WBO trip length	0.48	0.45	0.25				
OBO trip length	0.67	0.26	0.41	0.34			
Mean residential household income	0.05	(0.01)	0.06	0.02	0.05		
Residential density	(0.18)	(0.20)	(0.26)	(0.12)	(0.14)	(0.31)	
Workplace density	(0.13)	0.00	(0.18)	(0.09)	(0.10)	(0.21)	0.61

Looking at these variables in pairs, we see a few interesting results that confirm the findings of the cluster analysis above. First, unsurprisingly, the longer the average trip lengths for trips of various purposes, the higher the average total VMT. Interestingly, the "other based other" trips (or trips that go from someplace not home or work to another place not home or work) have the highest correlation. Both residential and workplace density are negatively correlated with total VMT. In Austin, the higher a resident's income, the more likely that resident is to live in a denser part of the MSA. The high positive correlation between residential and workplace density is interesting but probably overstated due to the number of work-from-home individuals in the set. In this matrix, income appears to matter little except as a predictor of density.

To explore the relationship between these variables further, I aggregated them by residential blockgroup, and then dropped all blockgroups with fewer than 7 residents in the data set, in order to highlight trends by blockgroup. I used the workplace density quintile as a factor (from 1 to 5) for each aggregation by residential blockgroup. This left 111,281 devices.

Using only residential density and workplace density quintile in a simple linear model to predict VMT per day for residents of a blockgroup yields an R^2 of 0.2364 (p-value: < 2.2e-16, all variables highly significant). Adding average household income by blockgroup only increases the explanatory value of the model by ~half a percentage point to $R^2 = 0.2418$. This lack of impact means, that at least in Austin, income is not strongly related to VMT beyond its impact on residential density.

Adding the average length of the commute raises the predictive power of the model again, but only to 0.37. Thus, we can say that even if we knew a residents' home block (with its inherent income and density statistics) and commute distance—three elements often collected in a workplace travel survey context—we could still only explain 37% of the VMT. Once again this highlights the importance in understanding non-commute driving. For comparison, if somehow a survey only collected homeplace (with its inherent income and density statistics) and other-based-other travel, they could explain 64% of VMT.

Finally, to visualize the results, I mapped the average total VMT for residents of each blockgroup in the Austin-Bergstrom MSA, as shown in Figure 1, below.

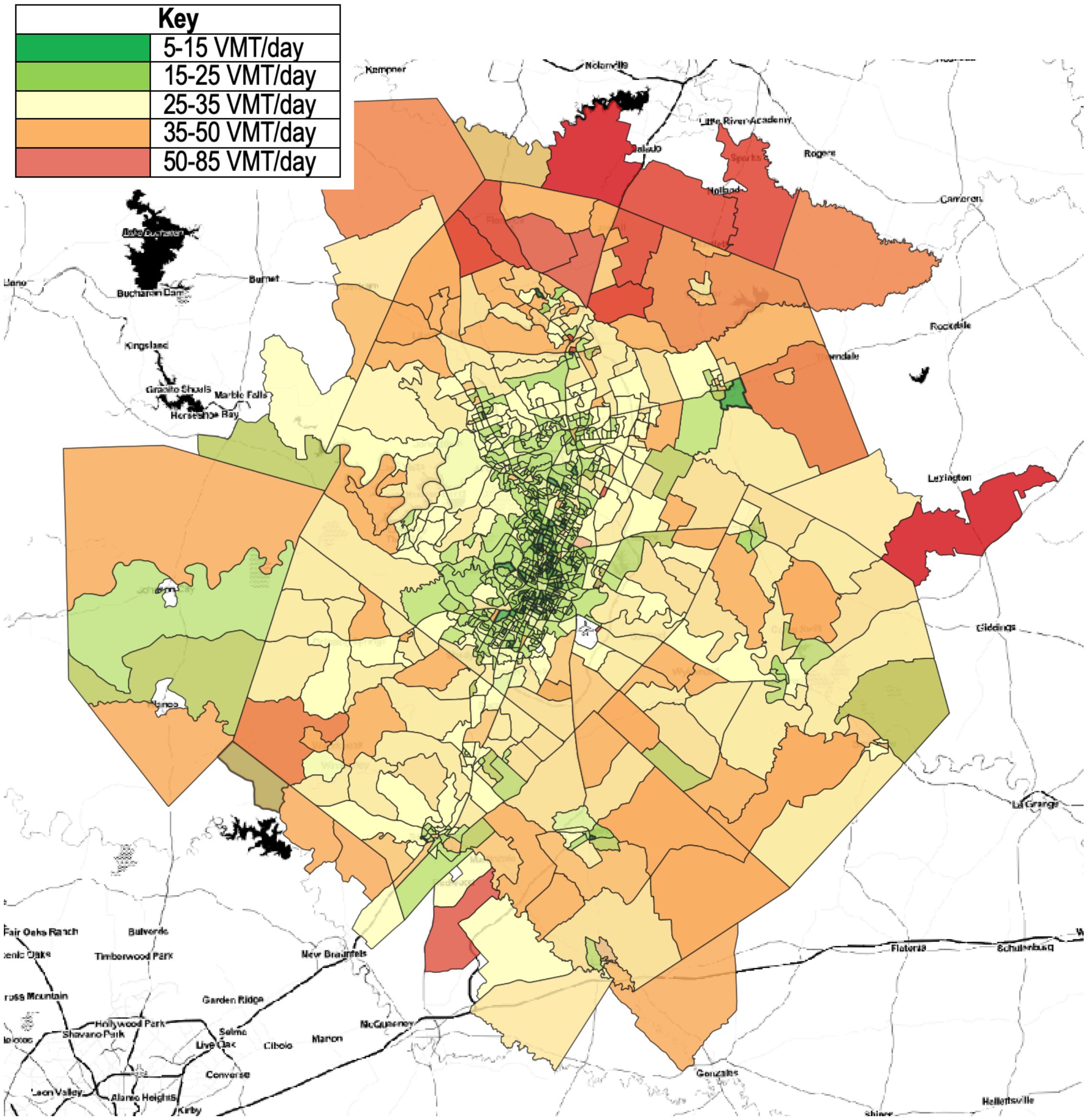


FIGURE 7.22: AVERAGE DAILY VMT FOR RESIDENTS OF EACH BLOCKGROUP IN THE AUSTIN-BERGSTROM MSA. THE RESIDENTS OF DENSER, DOWNTOWN AREAS, AS WELL AS SATELLITE DOWNTOWNS, HAVE LOWER DAILY VMT.

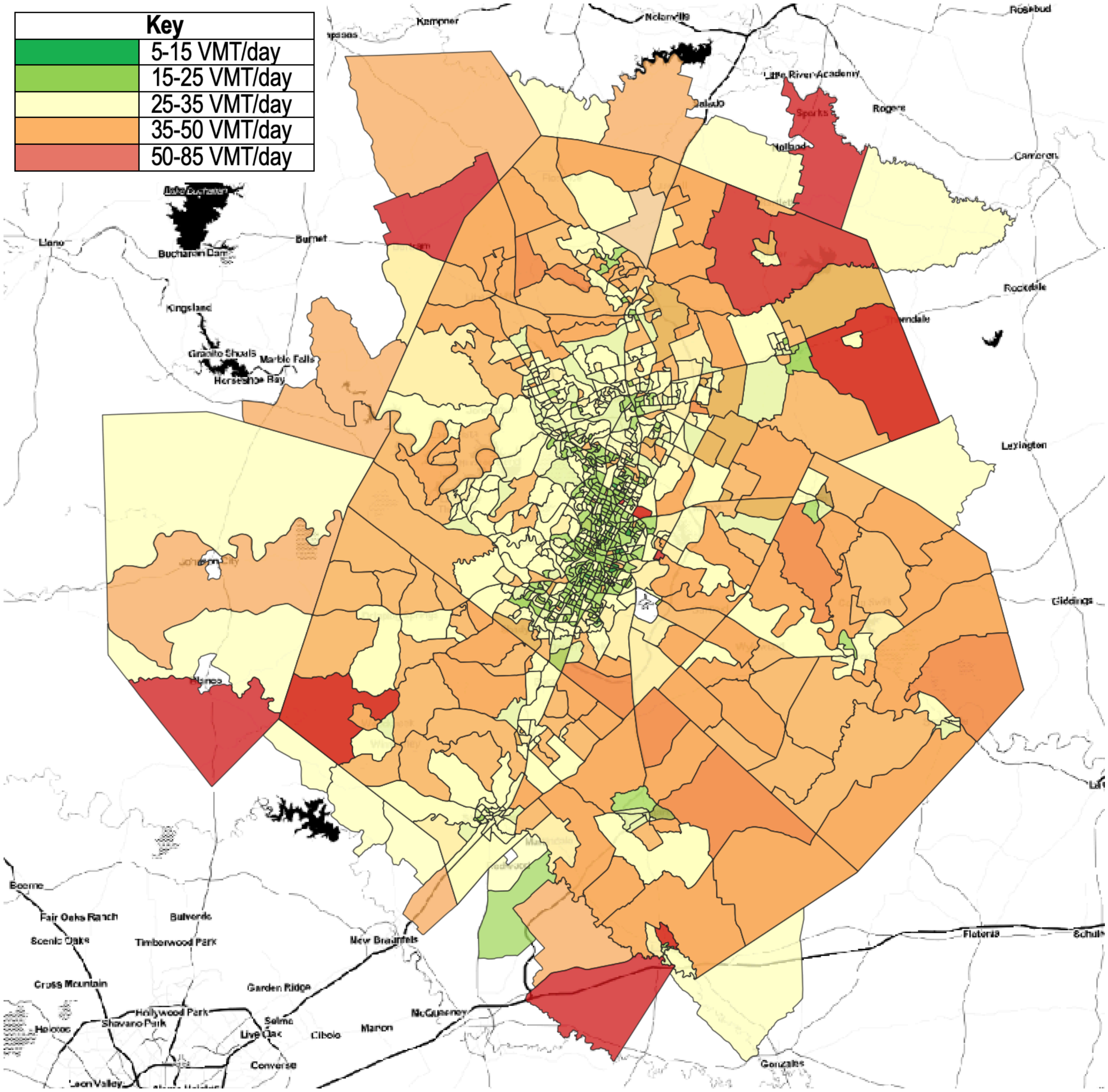


FIGURE 7.23: AVERAGE DAILY VMT FOR WORKERS IN EACH BLOCKGROUP IN THE AUSTIN-BERGSTROM MSA. THE WORKERS IN DENSER, DOWNTOWN AREAS, AS WELL AS SATELLITE DOWNTOWNS, HAVE LOWER DAILY VMT. HOWEVER, MORE OUTLIERS EXIST ON THIS MAP (LONGER COMMUTING DOWNTOWN BLOCKS) THAN IN THE RESIDENTIAL MAP ABOVE. THIS MAP INCLUDES PEOPLE WHO WORK FROM HOME, BUT NOT PEOPLE WHO HAVE NO FIXED WORKPLACE (PLUMBERS, TRUCKERS, UBER DRIVERS, ETC.)

7:E CONCLUSION

This research, by bringing a new data set to bear on a very old and complicated question. I find that using highly granular data that looks at a more integrated picture of an individual's daily travel is feasible, and yields results that support some of the existing literature and challenge other components.

The increased quantification can support more accurate predictions of the impact of policies and investments at a highly local level. Additionally, this level of granularity also reveals outliers – and outliers can be important. With this level of data, researchers can point policy maker to dive deep into positive case studies, and try to replicate the conditions. Or, as in the case of increasing VMT for non-traditional scheduled workers, the findings could be an important early flag about the VMT impacts of societal trends.

Several important questions were not addressed in this paper: the impact of self-selection on the relationship between density and VMT, the extensibility of these results beyond the Austin-Bergstrom area, and the role of transit as a less impactful form of VMT. Future work will tackle these questions.

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