Understanding the role of the forecast-maker in overestimation forecasts of policy impacts: The case of Travel Demand Management policies

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Understanding the role of the forecast-maker in overestimation forecasts of policy impacts: The case of Travel Demand Management policies

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ABSTRACT

Forecasting the impacts of a proposed policy is an important component of the transportation planning and decision making process. Although scientific tools are often used in transportation forecasts, biases and, more specifically, overestimations of the expected impact are often observed. This study explores the correlations between forecast-maker's characteristics and forecast bias creation and reduction. The study examines two transport-related policies aiming at the reduction of car use: telecommuting and carsharing. Both are Travel Demand Management (TDM) policies, which attract much attention from transport experts. We tested the extent to which the forecast-maker's beliefs about the policy at stake affected the forecast bias. We found that attitudes and beliefs associates not only with overestimation bias but also with its reduction over time. We also tested the extent to which the forecast-maker's affiliation, the performing institute and the publication type were correlated with the biases of the forecast and with the forecaster attitudes and beliefs. These characteristics are intuitively used by the forecast user as tools to assess the 'objectivity' of the forecast, but our analysis found no association between these characteristics and the forecast bias.

1. Introduction

Forecasting policy impacts play a significant role in the rational decision making process. Such forecasts lay the basis for ex-post policy evaluations and are perceived as an important scientific component of the policy rationale. However, although rigorous tools are used to predict policy impacts in many of the forecasts, biases in forecasts are well-known and empirical studies have found systematic biases associated with types of predictors and their clients (for example, a comparison between economic forecasts made by different actors and administrations was reported by Frendreis and Tatalovich (2000) and Baghestani (2008) compared unemployment rate predictions; Boylan (2008) found that the budget in a year ending right before an election was based on overly optimistic forecasts).

In fact, optimistic factors have also been identified in the private sector concerning a systematic overestimation of the success of projects and investments (Lovallo and Kahneman, 2003). The literature suggests three possible explanations for the underlying causes of such overly-optimistic predictions regarding the impacts of transport policies. The first claims that these overestimations are not biases, but simply errors which stem from the inherent uncertainty in the forecasting of future human behavior (Mierzejewski, 1996; Niles and Nelson, 2001; Richmond, 1990; Rodier et al., 2001). However, if this were true, we should observe both overestimation and underestimation forecasts, when in fact we see mostly overestimation (and hardly ever underestimation). The second explanation attributes overestimation to optimism bias, in which one's

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belief that a project or policy one is engaged with will be successful affects, consciously or unconsciously, the study results (Flyvbjerg, 2008). The third explanation attributes overestimation to deliberate bias, also known as strategic misrepresentation, in which one purposefully skews results to serve institutional and private needs. In many cases, overestimation results from a combination of optimism bias and deliberate bias (Mackie and Preston, 1998; Wachs, 1989). A similar explanation has been suggested by Laster et al. (1999) to rationalize the bias in economic forecast performance by private firms. In this case, the motivation for publicity overpowers the motivation for accuracy and results in biased forecasts. Although these explanations implicitly suggest that overestimation is associated with the type and the motivation of the forecasters, the role of the attitudes and beliefs of the people producing the forecasts on overestimation bias remain unclear.

The existing research on biased forecasts for the impact of transportation policies focuses on two major issues: mega-projects and public transportation (see for example: Meyer, 1999; Flyvbjerg et al., 2002; Flyvbjerg, 2008; Mackett and Edwards, 1998; Pickrell, 1990; Wachs, 1990). All biases have the same direction: overestimation of the benefit of transportation investments. Although briefly mentioned in a few studies (Howe, 1980; Brinkman, 2003; Wachs, 1990, 2001), overestimation in transportation policy has not been examined systematically as a factor of the people who are preparing the forecasts regardless of their organization affiliation.

This paper focuses on the professionals who make the forecasts (forecast-makers) and asks whether we can identify certain types of forecast-makers that are likely to produce over-optimistic forecasts, while other are likely to make less biased predictions. As we show later, over time the bias in predictions is reduced when different forecast-makers enter the scientific discourse. Therefore, it is interesting to examine various characteristics of the forecast-makers and test what are the characteristics that may explain the differences in forecasting. We examine two types of forecast-maker' characteristics. First, we test the impact of the forecast-maker norms and beliefs on the forecast results. We refer these norms and beliefs as "unrevealed characteristics" as these are hidden characteristics. The second type of forecast-makers' characteristics are referred as "revealed characteristics" since we can observe them easily. These include author affiliation, performing institute and publication type (scientific publication versus other types of publications). Forecast users (whether policymakers, scientists and others) usually tend to evaluate the quality and the objectivity of a research or forecast according to three determinants: salience, legitimacy, and credibility (Clark et al., 2006). These 'revealed indicators' are oftentimes the only indicators available to the readers. We test the common belief that a scientific product categorized as less biased, and explores potential gaps between the revealed characteristics of the forecast-makers and their norms and beliefs. Furthermore, this paper is the first to examine not only the factors that may be associated with creating the overestimation but also how forecast-makers who act to reduce overestimation bias affect the field.

We examine the correlation of the revealed and unrevealed forecast-makers indicators associated with overestimation of Travel Demand Management (TDM) impacts. TDM policies are transport-related policies aiming at reducing car travel. The studies of two TDM policies are examined: telecommuting and carsharing. Carsharing is a short-term car rental service which was first introduced in North America in the 1990s. Telecommuting, a much older policy, first suggested in the 1960s (NAE, 1969), is based on substituting commute trips with working from home using electronic communication, and refers to employees who can work from their conventional work place but instead work from home (Giuliano, 1992). These policies aim to change travel behavior and reduce the use of private vehicles by offering other mode of access. Therefore, forecasts and ex-post evaluations of the impact of these policies are concerned with the ability of telecommuting and carsharing to reduce car mileages. These predictions are at the heart of this study.

2. Background

2.1. Travel Demand Management (TDM)

The term "Travel Demand Management" was coined in the 1970s and is used to describe a wide variety of policies that focus on changing travel behavior and reducing car use on the existing transportation network. Meyer (1999) defines TDM as "any action or set of actions aimed at influencing people's travel behavior in such a way that alternative mobility options are presented and/or congestion is reduced". Although TDM has been an important tool in the effort to reduce vehicle miles traveled (VMT) for more than three decades, empirical studies imply that forecasts of the effects of TDM suggest a much greater effect than is actually measured (Giuliano, 1992; Bae, 1993; Marshall and Banister, 2000).

Models of the impact of TDM policies that analyze current impact and predict future behavior patterns are used extensively to plan transportation systems, forecast the effects of specific policies, and select alternative policies. Forecasting models can range anywhere from a simple "back of the envelope" type of calculation to a complex, regional travel demand model, depending on the needs and capabilities of the forecast-maker. Studies of the impact of TDM can result in a quantitative prediction based on models and assumptions regarding future rate of use, or a qualitative prediction that focuses on the impact without stating the quantified magnitude.

2.2. Who are the forecast-makers?

Planners, scientists, policy analysts, consultants, and other experts are only some of the people who carry out these forecasts. The characteristics of the people behind the papers and reports may have an important effect on the final results.

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Moreover, the characteristics of the experts often affect the credibility associated with the study. There is extensive research on the role of science in policy and the relationship between science and policy (for example: Weiss, 1977; Hoppe, 1999; Oreskes, 2004; Sabatier, 1998). However, scientific knowledge has as many facets as there are various actors, institutions and outputs that provide scientific knowledge. Moreover, scientists are not the only providers of professional information to the policy process. Weible (2008) uses the term ‘‘expert-based information'' to describe the ‘‘content generated by professional, scientific and technical methods of inquiries'' in the policy process. Such content providers may be policy analysts, scientists, or researchers in governmental or non-governmental organizations with various affiliations.

The utopian view of science and scientists sees them as above the social fray, using scientific methods to discover the truth, since their ‘‘entrenched skepticism'' ‘‘[leads] them to be epistemologically conservative and never make statements beyond what the evidence warrants, while the international nature of scientific methods of verification and systems of peer review act to prevent and remove any biases'' (Haller and Gerrie, 2007, p. 141). Such a naïve perception of science and scientists underlies the dichotomy often made between scientists and other professionals such as policy analysts, planners and journalists. For instance, Weimer and Vining (1998) characterize academic social science research as searching for the ‘‘truth'' as defined by the discipline, whereas other professions have a more identified and biased ‘‘client''. Wildavsky (1979) claims that ‘‘science is often described as organized skepticism'' (p. 206), demonstrating the expectation for scientists to be critical. Sabatier and Zafonte (1993) also criticize the ‘‘civic textbook view of the role of science,'' which identifies scientists as ‘‘neutral and seekers of the truth'' (p. 2).

A less utopian view of science and experts' role was presented by Sabatier as part of his coalition advocacy framework. Jenkins-Smith (1994) used the term ‘‘policy core belief'' to describe the basic normative commitment of individuals regarding a policy issue. Such a belief system is based on the policy goals of its holders and perceptions of important causal relationships and variable states. Since policy goals are usually complex and the ability to process relevant information is limited, policy core beliefs are affected by cognitive bias and constraints (Sabatier, 1998; Simon, 1956). In contrast to the stereotypical structure of decision making, which sees politicians as policy makers, and bureaucrats, and planners, researchers and other professionals as policy-indifferent, Sabatier stresses that they all have policy core beliefs.

The pure naïve perspective on science and scientists is rare in the public policy debate and often criticized. Nevertheless, when comparing scientists with other expert information providers (such as consultants and policy analysts) it is common to implicitly perceive scientists as more neutral, skeptical and unbiased, compared to consultants and policy entrepreneurs who are largely viewed as biased since they have visible and obvious interests and clients (Pickrell, 1991; Wachs, 1990, 2001).

There are several theories on possible overestimation biases in experts' work. Kahneman and Tversky (1979) view optimism bias as the outcome of the reflection of an individual's self-optimism in his/her work. Similarly, Lovallo and Kahneman (2003) refer to overestimation stemming from an ''inside view'' of the project at hand, a ‘‘planning fallacy'' which reflects the tendency to focus on the data and knowledge available on the specific project and to ignore less positive evidence from other sources. Oreskes (2004) claims that education, training and personal affiliation affect the way scientists weigh evidence. Moreover, empirical research has found that experts tend to be over-optimistic with regards to technological forecasts in their field, while they tend to underestimate the obstacles for adoption. The most pronounced bias has been found among experts working in the private sector (Tichy, 2004). In contrast, MacKenzie (1990) argues that scientists who are very close to a certain scientific field or very far from it tend to be skeptical about findings in that area, while those who understand the field but are not actually engaged in the research directly tend to be less skeptical.

How does optimism bias impact study results when non-deliberate manipulation is involved? There are many possible mechanisms by which optimistic beliefs can become an overestimation bias. The modeling process required many assumptions and decisions to be made about the data to be used, questions to be asked and answers and methods that each one may change the forecasting outcome. For example, Ascher (1978) emphasizes the role of underlying assumptions in the forecasting outcome. Assumptions, unlike collected data, can be selected by the expert based on his/her personal preference. Chalmers and Matthews (2006) present an example of a non-deliberate mechanism for optimism bias, namely citation bias, in which research with significant and positive effects of treatment is more likely to be published and cited. Such publication bias suppresses skeptical research findings, and therefore portrays an optimistic and biased representation of research in a field.

Other examples of possible mechanisms are confirmation bias and selection bias. Confirmation bias is the tendency to avoid seeking and considering data that disconfirms the individual's beliefs, and conversely, to more actively seek and better attend to and retain information that confirms one's beliefs. Selection bias can be manifested in two ways: first, in the individual's decision to work on a project or a policy that reflects her/his beliefs and second, in the tendency to select data that reflect the individual's beliefs similarly to the confirmation bias (Anderson, 2005; Landier, 2008). Tal (2008) suggests that a selection bias, the decision to produce a forecast for telecommuting in the early stages of research on the policy that was based on the policy potential, introduced optimism bias in early telecommuting studies.

3. Concepts and research hypotheses

In this study, we test potential correlations between unrevealed characteristics of the forecast-makers (beliefs and norms) and the forecasts they produce. We also test revealed attributes of the forecast-makers that are available to the forecast users (affiliation, institute and publication type). We examine two transport-related policies aiming at the reduction of car use: telecommuting and carsharing. Both are Travel Demand Management (TDM) policies that are expected to reduce vehicle travel and their impact have been studied and forecasts by mainly federal state and private organization. We choose to focus on those policies and not on a more local policies such as rail or other infrastructure projects to minimize the impact of local political impact on the forecasts that usually confined the forecast-maker into a set of assumptions not of her/his choice and may bias the forecasting results. All together we used 39 studies, which are not a sample, but include all of the available forecasts for telecommuting and carsharing impact as TDM policies in North America that we could found.

3.1. Forecasts of telecommuting and car-sharing

A 1978 study on the impact of telecommunication on transportation demand through the year 2000 estimated that telecommuting could reduce more than 10% of the total urban VMT when fully implemented. A 1991 study calculated the nationwide benefits of an expected 10–20% substitution of travel by telecommunications, mostly by telecommuting (Boghani et al., 1991). A 1993 study estimated that telecommuting could reduce total VMT by about 5% and could save about 826 million to 1.7 billion hours in traveling by 2002. Estimations of the actual impact of telecommuting by the year 2000 suggest an aggregate impact of less than 1% VMT reduction (Choo et al., 2005) and studies on the potential of telecommuting reveal a similar estimation (Mokhtarian, 1998).

Carsharing as a newer policy is promoted as an important sustainable TDM policy (see for example Shaheen et al., 1998) based on three arguments. First, carsharing is promoted as the missing link between public transportation and private vehicles (Cooper et al., 2000). Second, carsharing is represented as a way to change goods (the vehicle), into services, i.e., mobility (Manzini and Vezzoli, 2002). Third, carsharing is a way to move from fixed costs to variable costs (Steininger et al., 1996). The suggested positive effects of carsharing were based on the assumption that it would provide a substitute for the use of private cars but the evidence is mixed and suggests that in many cases, carsharing increases vehicle travel (Tal, 2009; Millard-Ball et al., 2005).

We claim that the results of some studies of carsharing and telecommuting forecasts have a component of overestimation bias, since all of the earlier forecasts explored in previous papers (Tal, 2008, 2009) did not materialize and the current accumulative impact of telecommuting and carsharing as TDM policies is almost negligible (see for example Martin et al. (2010) for carsharing impact and Choo et al. (2008) for telecommuting). As we show later (Fig. 1), evaluation studies have found that the actual number of telecommuters is significantly lower compared with most of the predictions.

3.2. Research hypothesis

This study explores the relationships between the forecast-maker characteristics (reveled and unrevealed) and the forecast results. We focus on the forecast-makers and not at the modeling process or modeling methodology since we assume that the methodology and the process are influences by the forecast-maker's characteristics.

The first hypothesis that we tested in this study is based on the theoretical layout of Sabatier (1998) regarding core beliefs. It suggests that the unrevealed characteristics of a forecast-maker, namely, his or her beliefs about the policy at stake are associated with the forecast of the policy impact. For this research, we constructed a typology with two *ad hoc* belief types that are based on the experts' beliefs towards the policy at hand. The first belief type refers to those who believe in the validity of the policy (as a TDM policy), while acknowledging missing evidence. The second type includes the skeptics. Webster's Dictionary defines skepticism as: "A critical attitude towards any theory, statement, experiment, or phenomenon, doubting the certainty of all things until adequate proof has been produced; the scientific spirit." In this case, one maintains a skeptical belief about the impact of a policy until definitive evidence surfaces. The skeptical belief is not necessarily a

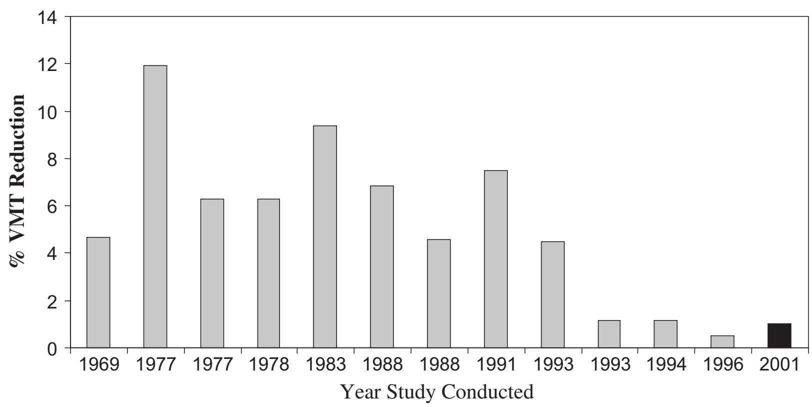

Fig. 1. Telecommuting forecasts and evaluation.

pessimistic belief in contrast to the optimistic attitude. The difference between the skeptical belief and the optimistic belief is based on the individual's attitude towards policy decision making under circumstances of uncertainty. Accordingly, this hypothesis concerns experts' beliefs about the policy. An optimistic belief regarding a policy's success as a TDM measure is expressed as "implement first, study later," and gives an optimistic presentation of the study results. A skeptical belief, on the other hand, is expressed as "more research is needed" and "the impact is unclear until proven otherwise." We expected to find a correlation between an author's belief about the policy and the forecast results. It was hypothesized that studies conducted by more optimistic belief holders would have an optimism bias.

The second hypothesis tests if revealed characteristics of the forecast-maker are associated with the forecasts results. We do not test causality, but whether affiliation of forecast-makers is a good proxy for forecast biasness. Following common wisdom, we hypotheses that scientists (as represented in the three aspects presented above) are expected to be more objective (i.e., have fewer bias components) than others (Steel, 2004). Consultants are expected to be loyal to their professional standards, but also to their clients, and are therefore considered less objective and are seen as having a higher propensity for bias (Brinkman, 2003). The revealed objective proxy variables explored in this study refer to visible and available information about the forecast-makers and the studies that are commonly used (implicitly) to evaluate the objectivity of a study and its credibility.

The third hypothesis in this study concerns the time sequences of the policy predictions. Optimists were expected to be the first to forecast policy impacts, while skeptics were expected to react and present lower estimations. It implies that different expert types play roles in different stages of the life cycles of the policy impact studies. Previous research (Tal, 2008) showed that overestimation bias is almost inherent in forecasting a new policy because of the methods, data, and knowledge available at that time, and that a reduction in overestimation occurs over time as more data becomes available and methods improve. First attempts to estimate the impacts of telecommuting for example, were based on aggregate data such as the forecast number of computer based jobs multiplied by their commute distance travel, and were focused on the policy maximum potential or potential market. Later, more detailed data, mostly based on surveys and pilot projects, enabled models that were based on preferences and actual behavior and were naturally lower than the maximum, as not all the potential telecommuters want or can pursue such behavior.

4. Research methods

Our analysis of forecast-makers focuses on the leading person in each forecasting effort (base on the order of authors in the relevant publication) and evaluating her/his beliefs about the policy in hand. It is assumed that this person has a major impact on the forecasting effort including framing the question, selecting the methods and data sources, etc.

4.1. Measuring policy core belief Indicators

The study's first hypothesis concerns the correlation between policy core beliefs and overestimation of the policy impact. Policy core belief as defined for this study is the general belief experts hold about whether or not a policy should be adopted (telecommuting or carsharing) as an effective TDM policy. Policy beliefs are based on the individual's knowledge of and experience with a specific policy, as well as one's attitudes and beliefs about broader policy matters, such as the need for governmental policies versus the free market. Forecast-maker's beliefs about the policy may be affected by the results of his/her current study, but is not likely to be based solely on the study.

Two methodologies were used to identify forecast-makers' beliefs in order to validate our categorization. First, semi-structured interviews with the forecast-makers themselves were conducted. Sixteen fully confidential interviews were conducted between 2006 and 2008, each lasting between one to 3 h. These interviews covered 28 out of the 39 evaluation and forecast studies (some authors led two or more studies). The interviews correspond to forecasts that were made between 1970 and 2007. The interviewees were asked about the changes in their attitudes and beliefs from the time they start working on the policy to the date of the interview. This way we overcome some of possible changes and adaptations in those attitudes and beliefs during the time, as it may filtered through their current knowledge and experience.

Based on the interviews, we classified the interviewees along two aspects that capture policy beliefs regarding the TDM that were studied and are hypothesized to be correlated to each other. Table 1 presents the two aspects that were tested. There are four potential types (resulting from 2 by 2 table). Type 1 and 4 are pure categories while 2 and 3 types are not conclusive.

At the end of each interview, the interviewees were also asked to classify themselves as optimists or skeptics. In most cases, the self-made classifications were consistent the categorization that was made by the researchers. In three out of the 16 interviews, the interviewees classified themselves as skeptics while their answers in the early stages of the interview pointed to more optimistic beliefs. In these cases, we chose their early statements as better representations of their beliefs at the time of the studies, since self-reported beliefs are more likely to incorporate current knowledge. In addition, we used the second methodology (detailed next) to validate our categorization and reduce the number of cases where neutral core belief was established. The authors of two press release documents were unknown and therefore they were not interviewed, but based on the rosy pictures the press releases portrayed, the anonymous authors' beliefs were set as optimistic.

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Table 1
Two aspects of the policy core belief.

		Motivation for the study	
		Looking for solutions	Testing TDM potential
Attitude towards earlier studies	Accepting earlier forecasts	(1) Optimistic	(2) Neutral
	Criticizing earlier forecasts	(3) Neutral	(4) Skeptic

Table 2
Hypothesis 1 – Revealed indicators.

Degree of biasness	Low	Medium	High
Position	Scientist	Consultant/specialist	Advocate/entrepreneur
Performing agency	Academia	Government	Other
Publication type	Scientific peer-reviewed journals	Reports	Other

We promised full confidentiality to the interviewee, many of them peers and collogues, in order to elicit the actual beliefs of the forecast-makers that otherwise may not have been revealed thus compelling us, in some cases, to aggregate interview results in our report, combining carsharing and telecommuting, in order to avoid interviewee identification.

The second method used to compliment the interviews by using qualitative content analysis of the introduction and conclusion sections of 24 evaluation or forecast studies. We used directed approach analysis, where categories are built a-priory (Hsieh and Shannon, 2005). In this analysis, performed by two readers, we searched for optimistic or skeptical statements about policies. Such statements are not directly derived from the study results, and in some cases even contradicted the results. In each document, two types of statements are assumed to reflect the authors' beliefs about the policy (optimistic, skeptical or neutral). The statements include the policy impact, i.e., whether the author endorse the policy impact as significant (referring to the policy as "promising", "revolutionary", "desirable", "innovative solution", "advantages", "dramatically reduce..."). In addition, we searched and the level of uncertainty about the policy impact, i.e., does the author present doubts about the level of data and knowledge used to assess the policy's expected impact (e.g., referring to the potential of the policy as "alleged", presenting statements as "Are these expectations realistic" with regard to previous studies or referring to the policy as "discussed as a strategy for reducing travel" and focusing on barriers). If an optimistic statement was followed by a statement indicating a high level of uncertainty, the author was classified as neutral. On the other hand, if the author avoided any impact statement, but did refer to a high level of uncertainty, s/he was classified as skeptical.

The final variable, the core beliefs about the policy, combined the two methodologies used. In cases where one measure was classified as optimistic or skeptical, and the other neutral, we reset the final variable to optimistic or skeptical. We have not had a case of an interview results that contradict the content analysis The neutral group includes forecast-makers that had beliefs about the policy which we failed to measure as well as forecast-makers that had no specific or significant beliefs about the policy in hand that would impact their research.

4.2. Measuring revealed indicators

Common wisdom holds that scientists are subject to less optimism bias and less intentional bias than consultants, and those consultants are less biased than advocates and entrepreneurs. According to this belief, we set the first research hypothesis. Table 2 offers three revealed operational indicators and the hypothesized level of biasness. The first indicator is the position of the lead forecaster (scientists, consultants and advocates/entrepreneurs). We categorized the forecast-makers according to their own definitions (during the interviews) and according to the affiliation presented on the study. For example, a consultant who also had a research position in a university was classified by the title she/he chooses to present on the paper. The second indicator is the performing agency, as stated in the papers (academia/public research institutes, government, and other). The third is the publication type (scientific peer-reviewed papers, reports, and others such press releases, brochures and publications that do not report on the data collection and research methods).

5. Findings

The most relevant variables in forecasting telecommuting as a transportation-related policy are the vehicle miles traveled (VMT) and the number of trips saved. These variables are directly derived from the number of telecommuters and the number of days they commute per week. TDM evolution and forecasting studies often focus on the potential of the policy to reduce the share of single occupancy vehicle traveling not in a specific year but in full deployment of the policy. Other studies that are focused on external changes such as the impact of the job market on telecommuting tend to anchor the forecast to a specific year. Fig. 2 demonstrates the changes in VMT reduction forecasts due to telecommuting from 1969 to 2002. The

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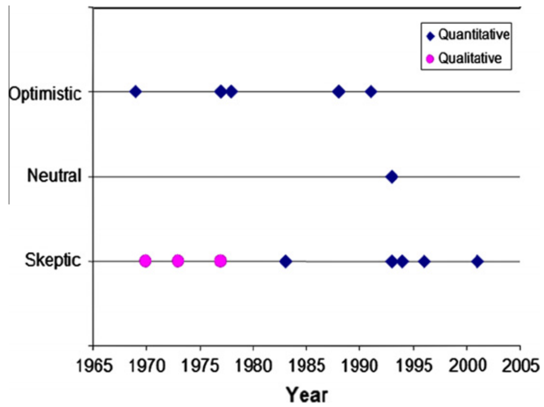

Fig. 2. Telecommuting evaluation over time.

forecasts (Fig. 1) are for the year 2000 or some undefined potential year in the future.[1] The last data point for 2001 (in black) is an evaluation study based on aggregate data, and is not a forecast (Choo et al., 2005). Except for the first data point, based on travel data from the 1950s, we see a significant reduction in forecasts over time and a reduction in variance in the data from the 1970s, the 1980s and the 1990s.

The carshare studies largely focus on the evaluation of current behavior, and only two studies forecast market size. None of the studies forecast the expected VMT reduction (a function of the market size and behavioral change), as often done in the case of telecommuting. The carsharing performance data include three variables that partially reveal the expected impact of the policy as report in Millard-Ball et al. (2006) and Tal (2009). The first variable is *VMT reduction per carshare user* in the United States, as reported by seven studies between 2000 and 2007. The change is reported in percentage point reduction in comparison to the pre-carshare VMT set at 100%. The studies included in the second variable point to the *number of vehicles replaced per carshare vehicle in service* as the main factor in explaining the variance of the results. A third way to measure the effect of carsharing is to determine the *percentage of users who reduced vehicle ownership*. This variable divides the reduced number of vehicles owned by carshare members by the number of carshare vehicles available. The result of this variable reflects not only the behavioral change of carshare members but also the operational decision of carshare companies on the number of cars to provide. Accordingly, the usefulness of this variable as a way to assess carsharing as a TDM policy is limited, but it is widely used to demonstrate the impact of carsharing, and is therefore included in this study.

Forecasts of VMT changes resulting from telecommuting suggested a reduction in the expected impact of telecommuting as a TDM policy over a span of 30 years. The carsharing studies, on the other hand, did not present forecasts of VMT reduction as did the telecommuting studies. Carsharing studies were mostly evaluation of current users' behavior. The variables presented suggested a positive impact resulting from carsharing, but the studies did not present a quantitative forecast of its aggregate impact as a TDM policy. Overall, as noted by Millard-Ball et al. (2005), the evidence about the impact of carsharing is limited and somewhat speculative. In contrast with the case of telecommuting forecasts, the partial evidence about the impact of carsharing as a TDM policy did not focus on VMT reduction but rather on changes in vehicle ownership, and newer studies have not shown reduction in the expected impact over time. Thus, when evaluating the telecommuting data for the first 10 years we see a similar picture of an unclear trend.

The forecast-maker's belief regarding a policy is measured in two ways. The first is based on the beliefs that can be derived from the written evaluation or forecast study which revealed the belief of the authors at the time of its writing. As mentioned, this measure was constructed through a semi-structured content analysis of the introduction and conclusion sections of each study. The second measure was based on interviews and reflects the beliefs of the main author in the year the forecasts were conducted but as reported during the interviews in 2006–2008. As described in Section 4, each measure has three possible values: *skeptical, neutral* and *optimistic*.

The statements used to classify the core beliefs are those which are not directly related to the study in hand, but relate more generally to the relevance and importance of carsharing and telecommuting as Travel Demand Management policies. An example of statements that reflect optimistic core beliefs is: "*At a minimum, telecommuting in particular, and teleworking in general, might allow cities to cope with increasing populations for a time without increasing investment in expanded transportation infrastructures*" (Nilles, 1988, p. 309). Skeptical core beliefs were identified based on statements such as "*Finally, in spite of these methodological concerns and the provisional nature of the data, there may be some very real transportation-based constraints that make it difficult at this time to replicate the European car sharing mobility effects in this country*" (Katzev, 1999, p. 71). While the optimistic statements mainly focus on the impact of the policy itself (for example, from an interview on March

[1] It is a common practice in the field of TDM to forecast the potential impact of full deployment of the policy with no target year or by using a long-range forecasting target. For many years studies of this type used 2000 which was later changed to 2020.

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13, 2007 "*I don't care about academic promotion. I am interested in making it work, not analyzing it to death.*" or "*Part of what we are doing is marketing*"), the skeptical statements are a mix between statements about the validity of the policy and about the validity of the data and knowledge used to come up with the forecasts (for example, from an interview on January 19, 2007 "*. . ..they were promoting telecommuting for more than a decade, and where is the research? Where is the evaluation?*").

The effect of the two core belief measures on the normalized results was tested using an analysis of variance. This test can be used as a guideline only, given the distribution of the normalized studies' results. The means reported show the impact of the policy using the same variables described in Section 4.1 (Table 3). The sample exhibits a lower reported impact by skeptics using both ways of measuring beliefs, consistent with expectations. The *F* test suggests an association between attitudes, as measured either in the texts or based on the interviews, and the forecasts and evaluations presented. This association may reflect the effect of core beliefs on the studies' results, or the impact of the studies' results on the core beliefs. It is most likely that both effects occur, but we cannot measure them separately.

The values of three revealed indicators of objectivity, assigned to each study based on available data, are described in Section 4.2. Four different measurements of the impacts of carsharing and telecommuting are used and presented in Table 3. In three of the studies, authors were not classified because of lack of data. The private companies' studies, usually reported as a press release, were classified as "other."

Each revealed measure category presented in Table 4 has a relatively small sample size (between 6 and 17, as shown by the gray column). To enable the comparison of bias across performance indicators using larger samples, we first normalized the impact variables so that the lowest value within the column subgroup was 0 and the highest value was 1. The 13 cases forecasting telecommuting VMT reduction, for example, computed to a value of 0 for the forecast of 1% reduction and a value of 1 for the forecast of 12% reduction, with the remaining 11 cases falling in between these two numbers.

Table 4 presents the means of normalized predicted policy impacts according to the various revealed objectivity indicators. The results indicate no reduction in the average relative impact for the presumably more objective categories of author affiliation and performing institute indicators. In the case of publication type, we see that academic publications report somewhat lower impacts compared with other publication types. The *p*-value presented in Table 5 is based on analyses of variance for each measure, examining whether the mean impact differs significantly by category. The results need to be treated as advisory only, as the sample is not normally distributed. Nevertheless, for all three variables, we see no strong support for the hypothesis that the reported impact significantly varied across levels within each 'objectivity' indicator.

Generally, the lack of support for the hypothesis (correlation between revealed measures of 'objectivity' indicators and the forecast results) can be explained in several ways. The hypothesis may be valid but the statistical tools fail to detect it, mainly because of the small sample sizes, or, the component of the bias may be smaller than the variation of the other

Table 3
Normalized study results by belief about the policy.

	Skeptical			Neutral			Optimistic			N[a]	*p*-Value
	N	Mean	SD	*N*	Mean	SD	*N*	Mean	SD		
Written belief	5	0.276	0.349	7	0.326	0.259	19	0.577	0.237	31	0.029
Interview based belief	7	0.179	0.281	10	0.396	0.284	16	0.564	0.309	33	0.025
Joint measure	9	0.28	0.32	6	0.45	0.36	23	0.53	0.29	38	0.028

[a] *N* represents the number of studies and not the number of forecast-makers. The joint measure includes five cases of missing interviews and five of missing interviewees.

Table 4
Studies by category.

Revealed objectivity indicators	Category	Carsharing percentage VMT reduction per user	Vehicles replaced per carshare vehicle	Carsharing percent of users who reduced vehicle ownership	Telecommuting percentage regional VMT reduction	*Total*
Author affiliation	Scientist	3	3	1	6	***13***
	Specialist	2	3	0	1	***6***
	Other	7	0	4	6	***17***
	Total	*12*	*6*	*5*	*13*	***36***
Performing institute	Academia	3	2	1	5	***11***
	Government and consulting	4	4	3	6	***17***
	Other	5	1	3	2	***11***
	Total	*12*	*7*	*7*	*13*	***39***
Publication type	Paper	5	3	2	3	***13***
	Report	1	2	1	10	***14***
	Other	6	2	4	0	***12***
	Total	*12*	*7*	*7*	*13*	***39***

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Table 5
Mean normalized study results by objectivity measure.

	N	Mean	SD	*N*	Mean	SD	*N*	Mean	SD	*N*	*p*-Value
Author affiliation	Scientist			Specialist			Other				
	13	0.467	0.323	6	0.434	0.111	17	0.434	0.327	36	0.948
Performing institute	Academia			Government			Other				
	11	0.444	0.325	17	0.361	0.361	11	0.436	0.580	39	0.193
Publication type	Scientific paper			Report			Other				
	13	0.368	0.270	14	0.441	0.288	19	0.530	0.374	39	0.437

Table 6
Objectivity indicator coherences.

	Author affiliation			Performing institute		
	Scientist	Specialist	Other	Academia	Government	Other
Performing institute						
Academia	9	1	1			
Government and consulting	4	5	8			
Other	0	0	8			
Publication type						
Scientific	8	3	2	9	4	0
Report	5	2	7	2	10	2
Other	0	1	8	0	3	9

variables, such as location and time frame. A third explanation may be that there is no actual correlation between the three suggested variables and potential biases.

An important check for the coherence of these objectivity indicators is a crosstab of all three indicators, as shown in Table 6. Full agreement between the three indicators should have resulted in all cases falling within the darker gray diagonals. Yet discrepancies are to be expected for consultants and specialists who may belong to more than one category. However, it was found that some discrepancies beyond those expected occur, such as between publication type and author affiliation. For example, there are two scientific papers written by authors with ''other'' affiliation.

Out of the nine scientists in the original dataset, five were also consultants, and three described themselves as advocates. The government and consulting category was also found to be a mixture of consulting firms and policy-oriented organizations that doubled as consultants for governmental agencies. The classification for a scientific paper versus a report had similar problems, as parts of five out of the 14 reports were also published as scientific papers.

These results, though not surprising, may be an important demonstration of the problem of relying on revealed characteristics of a study and its author when evaluating its objectivity and reliability. Often, researchers and other users who are familiar with the research and with the individuals conducting the studies can correctly anticipate the conclusions and recommendations of a study based on their familiarity with the lead author's views. The core belief classification presented in the next section suggests similar predictions based on somewhat less anecdotal evidence.

6. Discussion

An expert's belief that carsharing and telecommuting can have a valid positive TDM impact was found to be highly correlated with the result of the study. A simple explanation of this correlation may be that such an association is bi-directional, where these conscious or subconscious beliefs influence the produced or published results while, at the same time, the positive results create or reinforce existing beliefs.

It is interesting to find that optimistic authors, 45% of the sample, are found in almost all of the categories of indicators of objectivity, including scientists. It is even more intriguing to find that the seven skeptics in the sample (23% of the sample) include authors from all classifications including government and consulting, and other. The skeptic's belief, which mainly reflects the interpretation of the study's results, may cause a dissonance between the consultant's belief and the client's expectations, as observed by Brinkman (2003).

Our third hypothesis concerns the order in which optimists and skeptics enter the forecasting discourse and we hypothesized that skeptical forecast-makers enter the discourse just after the optimistic forecast-makers. However, our analysis so far is based on studies that result in a quantitative evaluation of the policy and does not include interviews with potentially skeptical researchers who focus on partial aspects of the policy or present their skeptical views qualitatively. Literature reviews of the early studies of telecommuting reveal evidence for early skeptical views, presented qualitatively rather than quantitatively. There are several thoughtful early examples of such qualitative skepticism that are not included in the

Table 7
The impact of beliefs on type of analysis over time.

	Timeline	
	New policy	Over time
Belief		
Optimistic	Quantitative Aggregate "Potential"	Quantitative Disaggregate pilot studies "Potential"
Skeptical	Qualitative "Limitations"	Partial analysis Disaggregate "Limitations"

analysis presented above because of the lack of quantitative forecasts. For example, in his dissertation, Harkness (1973) chose not to focus on telework and shop-at-home scenarios since he considered them less likely to occur. In an unpublished work cited by Jones (1973) and he questioned the success of telecommunication, saying that "urban transportation must look elsewhere for solutions to its congestion problems." Albertson (1977) came to a similar conclusion, stating that telecommunication is not likely to substitute for travel. None of these examples presented any supporting quantitative models.

The evidence on early qualitative skepticism in the case of telecommuting suggests that early skepticism will be qualitative at first and quantitative only later (Fig. 2). In this figure, 14 telecommuting forecast studies that took place between 1968 and 2001 are presented, showing that in the early stages of the explorations, skeptical studies are qualitative only while optimistic studies are quantitative. In this view, experts who hold an optimistic belief tend to start presenting the policy potential using aggregate data (see carsharing examples Litman, 2000 and Shaheen et al., 1998, or telecommuting examples Obermann, 1978 and JALA Associates, 1983). Subsequently, optimists are more likely to use disaggregate data and pilot studies to evaluate observed changes, while still emphasizing the policy potential. The skeptics, who started with qualitative analysis of the potential limitations, will also tend to move to disaggregate models, often focusing on one aspect of the policy's effect and on its limitations.

Table 7, presents the conceptual framework of new versus more mature policies as found in the case of telecommuting. Carsharing, on the other hand, may still be at the first phase of a new policy[2] and therefore we do not include it in the analysis.

Conventional wisdom contends that studies done by a scientist and published in a peer-reviewed journal are more likely to be objective, or less biased, than studies done by consultants or advocates. The hypothesis that these categories would produce a statistically significant difference in evaluations and forecasts of policies is not supported in this analysis. Table 5 suggests a partial explanation for the lack of correlation of the objectivity indicators by showing the differences within the three indicators that presume to indicate the same potential biases.

The interviews provided an additional explanation. In one interview, an advocate holding a research position (i.e., classified as a scientist) argued that for him, the forecast is mainly an advocacy tool, and not only the result of a modeling process. According to this interviewee, the reported forecast was produced in order to accomplish an advocacy need.

Discarding the hypothesis regarding the correlation between the revealed objectivity indicators and the reported forecasts and evaluations can help policy makers and other users of these studies to adjust their expectations about potential biases, but it does not help them understand the causes of the optimism bias phenomenon.

7. Conclusions

Classification according to optimistic and skeptical policy core beliefs may explain reduction in overestimation over time, as occurred in telecommuting, and may allow us to predict delay in reduction in the absence of skeptics in the process. Existing theories that focus on optimism bias and intentional bias can provide only a partial explanation of the reduction in forecasts over time. The results of this study suggest that experts are not homogeneous in their beliefs, and therefore, in the biases they introduce into their work. The introduction of skeptics, as a balance to optimists, suggests an explanation for such a reduction, even though it is a slow process.

It appears that the role of scientific skepticism is not only to point out the optimism bias but also to fill the gaps in data and knowledge. Research on the role of the beliefs of forecast-makers and researchers in general, and skeptics specifically, can help to better understand and reduce the impact of optimism bias and strategic misrepresentation that in many cases is unavoidable with new policies.

Furthermore for a policy maker, expert, journalist or layperson who reads a study or report in a field he is not familiar with, the affiliation of the author and the institute preparing the study are probably the only way to assess its objectivity. Similarly, even scientists tend to give higher credibility to scientific papers over other formats of publication. The results of this research imply that this classification may not be a valid indicator of potential bias in many cases because of biases that stem from beliefs that are not correlated with affiliation.

[2] In car-sharing, no early quantitative skepticism was found.

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This paper calls for a new way of classifying experts' knowledge in studies and for a consequent change in the use of this knowledge in the policy making process. It is also call for policies that will introduce studies lead by scientific skeptics in early phases of the policy introduction in order to reduce overestimation bias.

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