Project Report

Combining Disparate Surveys across Time to Study Satisfaction with Life

Prepared for **Teaching Old Models New Tricks (TOMNET) Transportation Center**

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16. Abstract

Satisfaction with life is a self-reported measure of the quality of life that has become a critical societal indicator extensively used for the evaluation and comparison of a wide range of trends and policies. This study fuses five cross-sectional travel surveys conducted from 1992 to 2018 across various geographical locations in California. Using the fused sample, we develop generalized ordered logit models to examine the effects of demographic characteristics, travel-related attributes, general and transport-related attitudinal variables, and context-control variables on individuals' self-reported measures of life satisfaction. We find that longer commute times, mobility limitations, and a tendency to see travel as a waste of time are negatively associated with life satisfaction. To enable the use of disparate cross-sectional survey data, we incorporate context-control variables into the models. We find that life satisfaction appears to be increasing as GDP per capita increases. Among employed people, the macro-scale unemployment rate positively influences their life satisfaction. Interestingly, all else equal, we find that online opinion panel respondents have lower life satisfaction relative to respondents from other sampling methods (mainly address-based sampling), a finding that should be considered in future research using these sampling methods. Overall, this study provides a unique look at life satisfaction within a transport context, while providing an example of fusing small-scale survey datasets to study longitudinal, domain-specific, influences on variables like subjective well-being.

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EXECUTIVE SUMMARY

Satisfaction with life is a self-reported measure of the quality of life that has become a critical societal indicator extensively used for the evaluation and comparison of a wide range of trends and policies. Various large-scale longitudinal studies have allowed researchers to model the effects of general variables such as demographic characteristics, as well as selected values and behaviors, on SWB. However, because these longitudinal surveys are broad in nature, they do not facilitate the examination of SWB within specific contexts or with the help of more diverse explanatory variables. As a result, researchers within assorted fields have taken to studying SWB using cross-sectional surveys, which are more commonly available and facilitate investigation from specific perspectives (e.g., effects of health, occupation, transportation, etc. on well-being). In this study, we combine the longitudinal and cross-sectional approaches to studying well-being, creating a fused dataset that includes common variables from five travel-behavior-oriented cross-sectional surveys conducted across the 27-year period from 1992 to 2018, across various geographical locations in California. Each survey includes an identical SWB question, as well as numerous other common variables across the individual datasets. Since these surveys were originally designed to serve travel behavior modeling purposes, the development of this fused dataset allows a unique examination of SWB within a transport context.

Despite the continuity of some design factors across the five cross-sectional surveys, there are inevitable inconsistencies stemming from question wording differences and evolving survey design techniques over the years. In this study, we demonstrate an approach for addressing and ameliorating such inconsistencies using a combination of survey fusion and model development techniques. As such, one contribution of this work is to provide a rigorous example of using multi-year cross-sectional survey datasets to study the longitudinal evolution of variables, in this case, SWB, over time. Accordingly, this study both: (1) provides a detailed examination of SWB from a general as well as a transportation-oriented perspective; and (2) provides an example of combining cross-sectional survey datasets for longitudinal studies.

Using the fused sample, we develop two generalized ordered logit models to examine the effects of demographic characteristics, travel-related attributes, general and transport-related attitudinal variables, and context-control variables on individuals' self-reported measures of life satisfaction. The first of these models uses all five surveys (the *full-sample model*), while the second model (the *attitudinal model*) includes three of the five surveys (1998, 2011, and 2015). The full-sample model includes a geographically and chronologically widespread sample, with which we focus on the examination of context variables such as GDP, unemployment rate, and sampling method. It maximizes the sample size, while the second model enlarges the set of common variables to include five transport-related attitudinal variables, at the cost of losing two of the five surveys. Besides these variables of particular interest (i.e., the contextual and attitudinal variables), we retain demographic characteristics and other travel-related variables in both models.

We find that longer commute times and lower incomes are negatively associated with life satisfaction; being female, more educated, living with others, and having a driver's license are positively associated; and (consistent with the literature) age has a U-shaped relationship (with life satisfaction tending to bottom out around age 44). Context-control variables enable us to combine disparate cross-sectional survey data sources, and we find that life satisfaction appears to be increasing as GDP per capita increases. Among employed people, the macro-scale unemployment rate positively influences their life satisfaction. Seven attitudinal variables, pertaining to lifestyle, personality, time use, and travel liking as well as perceived physical

limitations, have significant influences on life satisfaction, in natural and insightful ways. For example, mobility limitations, seeing cars as status symbols, and seeing travel as a waste of time and commuting as stressful are negatively associated with life satisfaction, while not minding being stuck in traffic is positively associated. These results suggest that the attitudes we could incorporate into the model are providing valuable glimpses of the role of one's outlook on life – status-oriented, impatient, even-tempered, and so on – in influencing one's satisfaction with life.

Interestingly, all else equal, we find that online opinion panel respondents have lower life satisfaction relative to respondents from other sampling methods (mainly address-based sampling), indicating that attitudinal differences may remain between respondents recruited in these diverse ways, even after controlling for demographic and other characteristics. This finding should be considered in future research using the increasingly popular online opinion panel approach to sample recruitment.

Overall, this study provides a unique look at life satisfaction within a transport context, while providing an example of fusing small-scale survey datasets to study longitudinal, domain-specific, influences on variables like subjective well-being. We urge early-career scholars conducting survey-based studies to begin now to consider the possibility of fusing multiple samples in the future, and with an eye to doing so, to give intentional thought to (1) specific questions that could be repeated in multiple surveys, and (2) the need for optimizing uniformity of question and response wording across surveys.

1. INTRODUCTION

In 2011, the United Nations General Assembly passed a resolution recognizing happiness and well-being as a fundamental human goal, and followed this in 2013 by establishing an official International Day of Happiness. These actions attracted much attention from the international community, and especially from those within academia, generating a surge of popular news and academic pieces on well-being and its variants. However, psychologists and social scientists have been studying happiness and subjective well-being (SWB) for decades based on large-scale longitudinal surveys. For example, Harvard Medical School's Study of Adult Development is the longest-running study of adult life (ongoing since 1939), and focuses on well-being during adulthood (McLaughlin et al., 2010; Waldinger et al., 2007). The World Values Survey (WVS) is another well-known longitudinal study, originating in 1981, spanning almost 100 countries, and spawning numerous contributions to the SWB literature due to its open availability (Kim, 2018; Sarracino, 2010). Other established sources of longitudinal well-being data include the British Social Attitudes Survey (BSA; Dean and Phillips, 2015), the European Social Survey (ESS; Welsch and Kuehling, 2017), the U.S. General Social Survey (GSS; Ifcher and Zarghamee, 2014), and the International Social Survey Program (ISSP; Levin, 2014).

These large-scale longitudinal studies have allowed researchers to model the effects of general variables such as demographic characteristics, as well as selected values and behaviors, on SWB. However, because these longitudinal surveys are broad in nature, they do not facilitate the examination of SWB within specific contexts or with the help of more diverse explanatory variables. As a result, researchers within assorted fields have taken to studying SWB using cross-sectional surveys, which are more commonly available and facilitate investigation from specific perspectives (e.g., effects of health, occupation, transportation, etc. on well-being). In this study, we combine the longitudinal and cross-sectional approaches to studying well-being, creating a fused dataset that includes common variables from five travel-behavior-oriented cross-sectional surveys conducted across a 27-year period. One of the authors of this paper was heavily involved in all five of these surveys, while another was heavily involved in the most recent three. Accordingly, each survey includes an identical SWB question, as well as numerous other common variables across the individual datasets. Since these surveys were originally designed to serve travel behavior modeling purposes, the development of this fused dataset allows a unique examination of SWB within a transport context.

Despite the continuity of some design factors across the five cross-sectional surveys, there are inevitable inconsistencies stemming from question wording differences and evolving survey design techniques over the years. In this study, we demonstrate an approach for addressing and ameliorating such inconsistencies using a combination of survey fusion and model development techniques. As such, one contribution of this work is to provide a rigorous example of using multi-year cross-sectional survey datasets to study the longitudinal evolution of variables, in this case, SWB, over time. Accordingly, this study both: (1) provides a detailed examination of SWB from a general as well as a transportation-oriented perspective; and (2) provides an example of combining cross-sectional survey datasets for longitudinal studies.

The remainder of this paper is organized as follows: Section 2 provides an overview of the SWB literature. Section 3 provides a short introduction to the five transportation-oriented surveys, describes the survey fusion process, and summarizes key statistics across the fused dataset. In Section 4, we provide background on generalized ordered logit (GOL) models and present our results using a GOL model. In Section 5, we discuss model findings and limitations. We conclude with a brief overview of major findings, and provide recommendations for future research.

2. LITERATURE REVIEW

2.1 Conceptual construct: from subjective well-being to life satisfaction

While the concept of happiness has long fascinated philosophers, positive subjective well-being as an academic field of study saw formal and widespread development starting in the 1970s (Diener, 1984). As an individualized measurement of well-being (Mokhtarian, 2019), SWB serves as a reflector of critical societal metrics such as economic development, social progress, and government policy (Diener, 2000). However, the definition and measurement of SWB are more complex relative to traditional social indicators like gross domestic product (GDP). Conceptually, SWB has been defined to have two main components: hedonic and eudaimonic well-being. Hedonic well-being (HWB) refers to pleasure attainment and pain avoidance, while eudaimonic well-being (EWB) is based on the idea of self-actualization (Ryan and Deci, 2001). In this study, we focus on a component of SWB, life satisfaction, which represents individuals' conscious evaluation of their lives (Pavot and Diener, 1993). Traditionally, life satisfaction has been considered a component of HWB; however, Huta and Ryan (2010) showed that life satisfaction may be related to both hedonic and eudaimonic perspectives of SWB.

Life satisfaction (along with other SWB components) is typically measured using either single-item or multi-item methods, each of which has differing strengths and limitations (Diener, 1984). Single-item measures refer to short, clear survey items that can be implemented independently of other items. The simplicity of single-item measures requires less effort from respondents and survey developers, which makes them more suitable for inclusion in non-SWB focused surveys. In contrast, multi-item measures, such as the Satisfaction with Life Scale (SWLS), are composed of a group/set of survey questions, thus allowing researchers to check internal consistency and/or quality of responses, and to obtain a richer, more-nuanced, measure. The dataset used in this study is derived from a series of travel-behavior oriented surveys, and uses a single item to measure respondents' satisfaction with life. Recent literature has shown that single-item measures of life satisfaction perform similarly to the multi-item measures in SWLS studies (Atroszko et al., 2017; Cheung and Lucas, 2014; Jovanović, 2016); and furthermore, Diener (1984), one of the SWLS developers, recommends the use of single-item scales when a brief measure of global well-being is needed, noting that they provide adequate validity and reliability for such purposes.

2.2 What influences SWB[1]? Some empirical results

Here, we summarize findings from the literature on the effects of (1) demographic characteristics, (2) travel-related attributes, (3) personality and attitudinal variables, and (4) contextual variables (e.g., GDP per capita) on SWB, focusing particularly on these four subgroups of explanatory variables as these were the ones available in the study at hand. Furthermore, some of these variables are among the most widely studied explanatory factors for life satisfaction in the literature, aside from domain-specific factors such as health, occupation, and community/ friendship. Although the latter have also been found to influence SWB measures, we do not explore them further given that they are not within the scope of this study.

2.2.1 Demographic characteristics

Behavioral researchers across disciplines often begin their modeling efforts with the inclusion of

[1] In this section, we use SWB to broadly refer to multiple terms related to well-being evaluations, including subjective well-being, happiness, and life satisfaction. This is largely because scholars often use these terms interchangeably in different domains, thus precluding any attempts to disentangle the results (Gärling & Gamble, 2018).

demographic characteristics, and as evidenced by a wide body of literature, SWB is no exception. Relative to other demographic characteristics, *income* tends to be of primary interest in SWB studies since it is an indicator of numerous other critical variables such as education (Diener and Biswas-Diener, 2002), health (Marmot, 2002; Pickett and Wilkinson, 2015), and housing (Hansen et al., 1998). In addition, studies have shown that income has interactions with age (Deaton, 2008) and household structure (Cracolici et al., 2014; Cummins, 2009). As expected, these findings converge on the understanding that income has an overall positive effect on life satisfaction, with higher-income populations having higher levels of well-being, and lower-income populations seeing the greatest potential for increased levels of well-being due to their incompletely met basic living needs (Cheung and Lucas, 2014; Deaton, 2008; Diener and Oishi, 2000; Helliwell and Putnam, 2004; Pickett and Wilkinson, 2015; Stevenson and Wolfers, 2008). In higher-income countries such as the U.S., which is the context of this study, the *age* effect on SWB has a U-shaped pattern across the life cycle when cohort effects are controlled: i.e., the lowest life satisfaction occurs among the middle-aged population (Blanchflower and Oswald, 2008; Deaton, 2008; Helliwell and Putnam, 2004; Shields et al., 2009; Welsch and Kuehling, 2017).

In contrast to the stable patterns identified thus far for income and age, the relationship between SWB and *education* is less consistent. For example, some studies report that education positively influences SWB, with higher-educated people having higher SWB (Helliwell and Putnam, 2004; Nikolaev, 2018; Witter et al., 1984; Yakovlev and Leguizamon, 2012), while others report negative and/or insignificant effects of education on SWB (Kim, 2018; Nikolaev, 2015; Shields et al., 2009). *Family structure* is another key demographic variable, with studies finding that being married increases life satisfaction (Diener et al., 2000; Shields and Wooden, 2003), and researchers finding that in general, interactions with family members have positive effects on SWB (Hartley-Clark, 2014; Helliwell and Putnam, 2004).

2.2.2 Travel-related attributes

In recent years, SWB has attracted increasing attention in the transportation domain, with De Vos et al. (2013) conceptualizing a seminal framework of ways in which travel behavior may affect SWB, namely via (1) experiences during (destination-oriented) travel, (2) activity participation enabled by travel, (3) activities during (destination-oriented) travel, (4) travel as an activity, and (5) the potential to travel. In practice, the majority of the empirical literature has focused on examining the effects of behavior related to the *commute* (defined as the trip from home to work/school, and back) on SWB.

While numerous studies (Hilbrecht et al., 2014; Martin et al., 2014; Nie and Sousa-Poza, 2016; Stutzer and Frey, 2008) have reported that increased commute time is negatively associated with SWB, others (Dickerson et al., 2014; Lorenz, 2018) find that commute time is unassociated or even positively associated with SWB. For example, Sweet and Kanaroglou (2016) find that commuting indirectly increases SWB by enabling activity participation. Regarding travel mode, active modes such as cycling and walking are seen to have large positive effects on SWB in general or satisfaction with travel in particular (Martin et al., 2014; Morris and Guerra, 2015; St-Louis et al., 2014). In contrast, car commuters have been found to experience increased stress due to mental strain and traffic congestion (Wener and Evans, 2011). However, potentially due to differences in local transit services and roadway infrastructure, there are conflicting findings regarding whether car or transit commuters are more satisfied (Eriksson et al., 2013). Nonetheless, among all modes, drivers are least likely to obtain hedonic benefits and most likely to obtain cognitive disadvantages as a result of travel-based multitasking. In the same vein, transit passengers are more likely than

other mode users to experience both hedonic and productive benefits from travel-based multitasking (Shaw et al., 2019). Thus, we might see that the effects of mode choice on SWB are moderated by mode attributes such as quality of the available service and opportunities for multitasking.

2.2.3 Personality and attitudes

While we have thus far examined external characteristics such as demographic characteristics and travel attributes, underlying traits such as personality types and attitudes also have significant impacts on SWB (DeNeve and Cooper, 1998; Diener et al., 2003). Unlike manifest/external characteristics, personalities and attitudes are latent, individual measures that can have wide-ranging impacts on a broad array of responses such as dominance, sociability, emotional stability, and trust (Ajzen, 2005). Personality traits may influence SWB *directly* with certain traits (e.g., extraversion, neuroticism) resulting in different experiences of positive/negative affects, or influence SWB *indirectly* by guiding people's behaviors and the resulting outcomes (Soto, 2015). Attitudes are latent constructs that represent a person's perspective on specific aspects of life (Ajzen, 2005) such as education, environment, and transportation, to name a few. Life satisfaction is also an attitudinal construct, which reflects one's perspective on/assessment of life (Heller, Watson, and Ilies, 2006).

Thus, latent factors such as personality orientations and attitudes can help researchers to understand and explain SWB using internal characteristics that can potentially represent motivations and values. Numerous researchers have included personalities and attitudes in their models to better explain SWB. For example, Helliwell and Putnam (2004) show that those who believe themselves to live among trustworthy people report higher SWB. McCarthy and Habib (2018) find that community-mindedness positively influences SWB, while people who take pride in owning a car have higher SWB. Thus, we see that personalities and attitudes can aid in better understanding different levels of SWB among individuals.

2.2.4 Context-control variables

Empirical research by Lucas and Donnellan (2007) has shown that one third of the variance in life satisfaction exhibits complete stability over time, with another one third of the variance showing moderate stability, and the remaining instability attributable to contextual circumstances.

Many longitudinal studies have examined SWB trends over time. For example, Blanchflower and Oswald (2004) found that happiness declined through the last quarter of the twentieth century in the U.S.; however, they found almost no change in Great Britain during the same time period. More recently, Ortiz-Ospina and Roser (2018) analyzed SWB trends from the World Value Survey (WVS) and found that 49 of 69 countries have positive happiness trends over time (1984-2014). Other findings also show that SWB differs across regions. For example, Morrison and Weckroth (2018) found that metropolitan inhabitants of Finland had significantly lower average life satisfaction than their non-metropolitan counterparts. In a more nuanced report, Requena (2016) concludes that in wealthier countries, those living in rural areas have higher levels of SWB relative to those living in urbanized centers, while city dwellers in less prosperous countries have higher SWB relative to their counterparts in lower-density regions.

To study the contextual effects on SWB in a more systematic manner, many researchers include specific context-control variables in their models. Specifically, such variables might include GDP (gross domestic product, Diener et al., 2010), unemployment rate (Di Tella et al., 2001; Ochsen, 2011), social inequality (Kelley and Evans, 2017), democratic governance (Frey

and Stutzer, 2000), geographic characteristics (e.g., sunshine hours) (Oswald and Wu, 2010), culture (Oishi, 2006), etc.

For longitudinal across-region SWB surveys, the best case is to use consistently designed surveys such as WVS. However, such resources will commonly not exist if researchers want to study SWB with specific domain variables. Given that we used a fused dataset developed from five travel-behavior oriented surveys, there were differences in sampling methods across component surveys. Based on literature showing that stratified samples from online panels are not representative of the entire population regarding demographic characteristics, attitudes, and behaviors (Blasius and Brandt, 2010; Fan and Yan, 2010; Szolnoki and Hoffmann, 2013), we introduce a context variable to control for varying sample sources.

To summarize, in this literature review section, we introduced SWB as a conceptual construct and discussed prominent measurement philosophies, providing a basis for our use of a single-item measure for life satisfaction. We then drew from the literature to better understand the effects of demographic characteristics, travel-related attributes, personality/attitudinal constructs, and contextual variables on SWB, providing a foundation to better understand the models developed for this analysis.

3. OVERVIEW OF DATA

3.1 Cross-sectional surveys

This study utilizes a fused dataset of five California-based, transport-oriented cross-sectional surveys covering a 27-year period from 1992 to 2018. These five surveys were selected for this specific analysis as they all contained the same life satisfaction question, which is the key dependent variable in this study, and were implemented within California creating homogeneity of geographic context. One co-author of this paper was responsible for or integrally involved with the survey design, development, and implementation processes across all surveys considered for this data fusion process, while other co-authors were responsible for or integrally involved with one or more of them. Table 1 provides an overview of key characteristics of the surveys; here, we discuss these characteristics, providing additional context regarding the original goals and distinctive features of each survey.

The earliest survey, conducted in 1992, was deployed with the overarching goal of studying telecommuting, then defined as the concept of working from home or a location closer to home, thus eliminating the need to travel to and from work (i.e., commuting). Telecommuting was hailed as an exciting game-changer in the early 1990s, and seen as a strategy for reducing congestion and emissions. The survey was deployed to six of twenty-seven departments in the City of San Diego, California, and all regular employees within those departments were surveyed. This convenience sampling method was not used in any of the remaining five surveys, and resulted in a very high response rate of 44% (Mokhtarian and Salomon, 1996).

The next survey in the series was conducted six years later in 1998, and was deployed with the intention of measuring the existence and impact of positive attitudes toward travel itself (particularly local daily travel), in contrast to the conventional view of travel as a disutility, undertaken purely for instrumental reasons of reaching a desired destination. This survey used address-based simple random sampling across three San Francisco Bay Area neighborhoods with diverse land-use, travel, and demographic patterns; the overall survey had a response rate of 24% (Curry, 2000). Although surveys involving the same investigator that were conducted in 2003, 2006, and 2009 were also considered, the next one with enough commonalities to be included in the fused dataset of this current study occurred in 2011.

The 2011 survey focused on multitasking during commute travel (i.e., attitudes and behaviors related to travel-based multitasking). This survey used several sampling methods (see Table 1) with the goal of obtaining sizable (rather than representative) shares of all pertinent means of travel (modes). Survey distribution channels included physical distribution on public transit, employee/student email lists from organizations including a large university, a large email list of Sacramento-area commuters interested in alternatives to solo driving, email and mailing addresses purchased from commercial marketing companies, and survey links posted on transportation agency and corporation websites. Where measurable, response rates across the various sampling channels varied from 0.23% to 18.2% (Neufeld and Mokhtarian, 2012).

The next survey included in the dataset was conducted in 2015, and focused on the mobility choices of Generation Y (Millennials, born in 1981-1997) and Generation X (born in 1965-1980). This study used an online opinion panel, and applied a quota sampling approach using targets for gender, age, race, ethnicity, household income, and presence of children in an effort to ensure diverse representation of the population in California. Because the respondents were paid members of the online panel, this sampling method resulted in a very high response rate of 46.3% (Circella et al., 2016).

The final survey included in the fused dataset was fielded in 2018, which is the second wave of the 2015 survey. The 2018 survey aimed to study the impacts of emerging technologies (e.g., ride-hailing services, autonomous vehicles) and transportation trends through a unique longitudinal approach. Specifically, part of the sampling frame of the 2018 survey came from the 2015 survey respondents. Among the re-contacted respondents, 246 people completed the 2018 survey. The rest of the 2018 survey respondents were recruited through two sample frames: a stratified, address-based random sample, and a quota sample from an online opinion panel (Circella et al., 2019).

Table 1. Overview of cross-sectional surveys that comprise the fused dataset

Year	Survey focus	Location	Sampling method	Completion channel	Response rate[1]	Working sample size[2] (N)
1992	Telecommuting	Southern California	Convenience sampling (at a single employer)	Paper	44%	601
1998	Positive travel utility	Northern California	Simple, address-based, random sampling within three diverse neighborhoods	Paper	24%	1,317
2011	Travel-based multitasking	Northern California	Convenience sampling (on-site physical distribution, university staff and student emails, other online); simple random sampling, email addresses within study areas, address-based; quota sampling, online opinion panel (Survey Analytics);	Paper, online	5%[3]	2,415
2015	Mobility choices of millennials and Gen X	California	Quota sampling, online opinion panel	Online	46%	1,155
2018	Impacts of emerging technologies and transportation trends	California	Stratified random sampling, address-based; quota sampling, online opinion panel; convenient sampling, recall of respondents from 2015 survey	Paper, online	7.01%[4]	2,026

[1] For initial samples, which have been filtered for the purposes of this study.
[2] For the purposes of this study; comprises workers who commute.
[3] Composite across the methods for which a rate could be computed; in some cases the denominator was unknown or (e.g., in the case of links posted to a website) not applicable.
[4] The response rate is derived from the stratified address-based random sample (1,992 responses from 30,000 invitations) and the recall of respondents from the 2015 survey (246 responses from 1,939 invitations). The number of invitations for the online opinion panel was not provided by the panel vendor.

3.2 Data fusion process

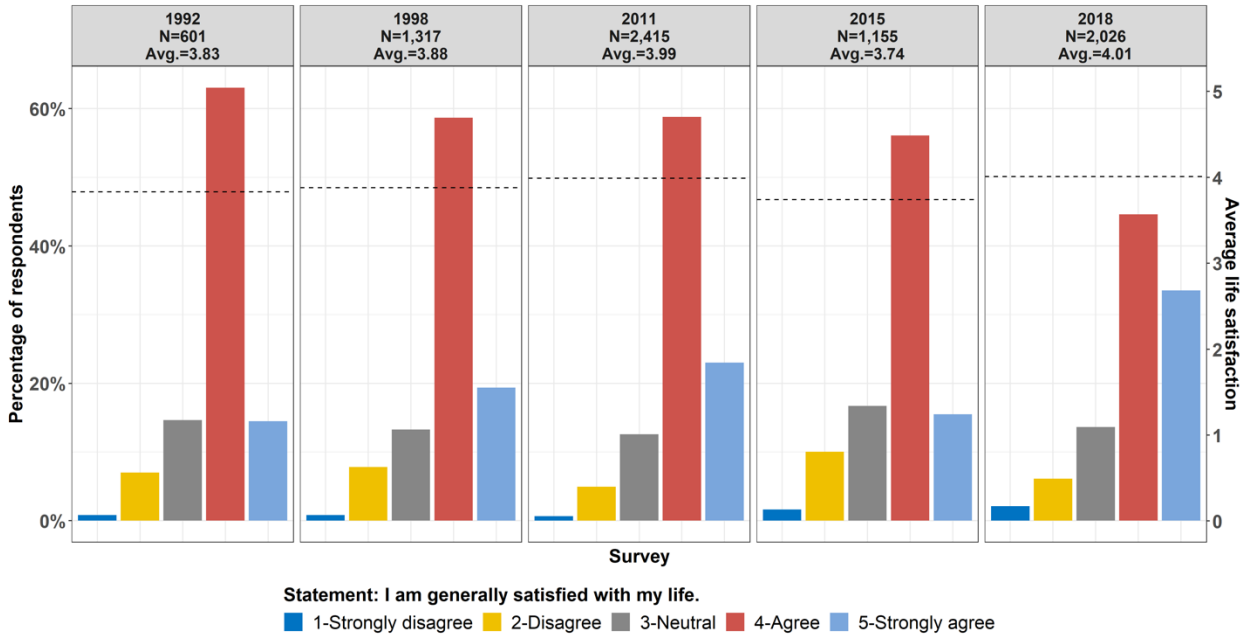
To facilitate the process of fusing the surveys discussed in the preceding section, we first developed a question "inventory" spreadsheet, which included all survey questions and possible response choices across the surveys. Next, we categorized the survey questions using a four-level hierarchical classification system, the first level of which specified a general, broad category for each survey question. General categories include attitudes, socio-demographic characteristics, travel attributes, land use characteristics, and specific survey focused questions. Next, we categorized each survey question according to its specific topic; for example, general values, environment, lifestyle, travel, time use, work, etc. The remaining categories in the hierarchy simply specified in greater detail what aspect of the topics are covered in each question. This hierarchical labeling system then allowed us to group questions that convey essentially identical meanings based on content and possible answer choices, while allowing for minor wording and formatting differences. In the next section, we provide descriptive statistics for the dependent variable in this study (i.e., satisfaction with life), as well as the common explanatory variables used across the surveys, and detail some of the adjustments that were made to facilitate this data fusion process.

3.3 Variables used in the study

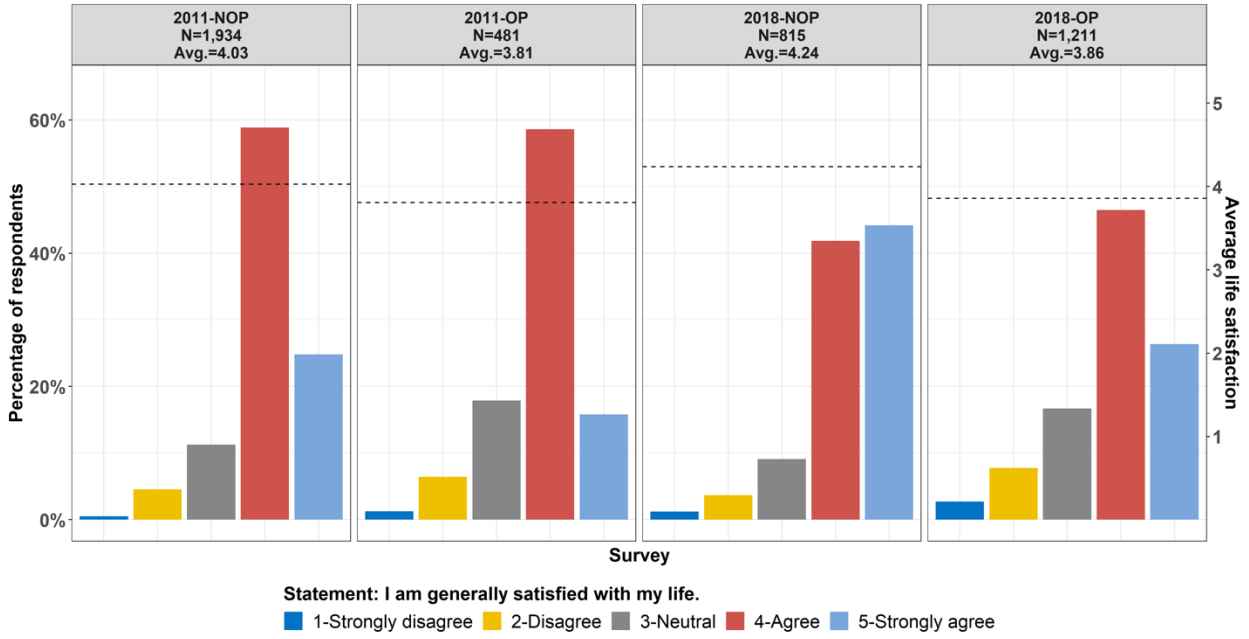
For the purposes of this analysis, we restrict our sample to commuters only (i.e., workers who travel to and from work), to increase the homogeneity of context across all survey datasets. Furthermore, by filtering out the non-workers, we are able to retain more travel-related variables in the model. After removing inattentive and incomplete cases, the final fused dataset comprises 7,514 valid cases for use in this study (see Table 1 for sample size by survey). Each of the five surveys obtained life satisfaction ratings by asking respondents to rate the statement "I am generally satisfied with my life" using a five-point Likert-type response scale ranging from strongly disagree (1) to strongly agree (5).

Figure 1(a) presents the life satisfaction rating distribution for each survey, and illustrates that there is an increasing trend over the years with the exception of the survey conducted in 2015 – which only used an online opinion panel to sample respondents, and also had the narrowest age range. This observation prompted us to compare the group of all opinion panel respondents (part of the 2011 and 2018 sample [Figure 1(b)], and all of the 2015 sample) to everyone else, and we found that there was a significantly lower mean life satisfaction ($t = 9.326$, d.f.=5450.8, $p < 0.001$) for the opinion panel group. However, because recruitment via an opinion panel (particularly in 2015; see Section 3.1 and Table 1) is somewhat confounded with belonging to age groups whose SWB might be expected to be lower than average (Millennials having entered the workforce during a major recession, and Gen Xers being near the bottom of the U-shaped relationship of age to SWB as described in Section 2.2.1), we revisit this effect in Section 4, using generalized ordered probit models that control for age and other variables. The overall mean for the fused dataset was 3.92 (out of 5).

Figure 2 presents the life satisfaction rating distribution by region. We see that among the three California regions, Northern Californians have the highest average life satisfaction, followed by Southern Californians and respondents from "other" California regions.



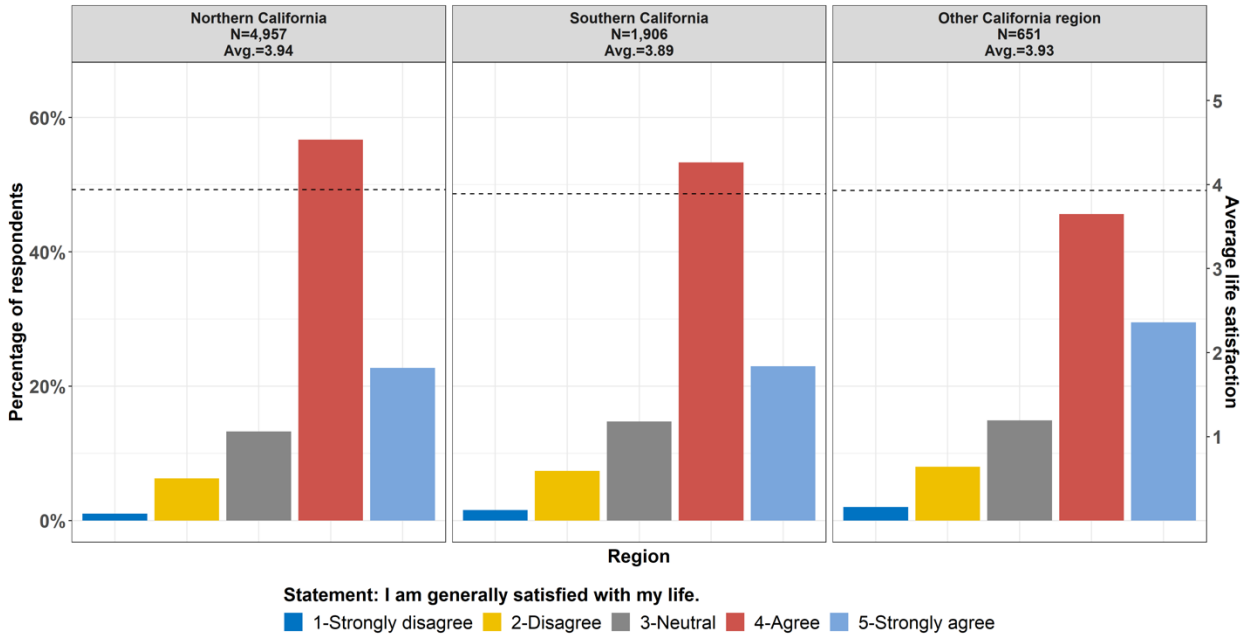
(a)



(b)

Notes: For the 2011 and 2018 surveys, "OP" represents the survey respondents from the online opinion panel, whereas "NOP" represents the rest of the survey respondents. The 1992 and 1998 surveys did not recruit respondents from the online opinion panel, while the 2015 survey respondents are all from the online opinion panel.

Figure 1. Distribution of self-reported ratings of life satisfaction by survey



Notes: Northern California includes the Sacramento Area Council of Governments (SACOG) and Metropolitan Transportation Commission (MTC) regional planning areas. Southern California includes the Southern California Association of Governments (SCAG) and San Diego Association of Governments (SANDAG) regional planning areas.

Figure 2. Distribution of self-reported ratings of life satisfaction by region

Table 2 summarizes descriptive statistics for the explanatory variables used in the models, which are presented in Section 4. Prior to executing the models, it was necessary to transform several variables to obtain a consistent scale across surveys. For example, the original five surveys have different household income categories to reflect income distributions at the time of survey implementation. For this modeling effort, we used the mid-point of each income category from the original surveys and converted this to the equivalent purchasing power in June 2018 (the implementation date for the last survey in the fused dataset). To do this, we used the consumer price index (CPI) from the Bureau of Labor Statistics to convert all category midpoints to "2018 dollars", after which we classified the converted household incomes into the six income categories used in the 2018 survey, in keeping with the need for consistency across surveys. The income distribution after conversion is shown in Table 2. This is detailed here as an example of the types of consistency conversions necessary when fusing cross-sectional surveys across time.

To further simplify model development, we treat income and education as continuous variables in the models. The original age statistics for each survey are listed in Table 2. In the modeling portion of this paper, we use mean-centered age to provide more natural interpretations of the impact of age (by considering changes from the mean age rather than changes from 0 years old). Table 3 shows the slightly differing statements representing the five attitudinal variables retained in the fused dataset; respondents were asked to rate the statements using a five-point Likert-type response scale. We also note that similarly modest differences in wording exist not only in the attitudinal statements, but also in survey questions that obtain demographic and travel-related characteristics. We acknowledge that the subtle differences in wording between the surveys may influence respondents' final responses, but note that such differences will be common consequences of fusing disparate datasets. We also exercised what we believe to be conservative

judgments about the extent of differences that we considered acceptable; i.e., we eliminated questions/statements that we considered likely to result in rating differences across surveys. As a result, all retained variables are believed to convey the same *meaning* to respondents across surveys, although slight variations in wording are still present.

Table 2. Descriptive statistics for variables common across surveys

Variables	1992		1998		2011		2015		2018		Full sample		ATT subsample[1]	
	N=601		N=1,317		N=2,415		N=1,155		N=2,026		N=7,514		N=4,887	
Continuous variables	$\bar{X}$	s.d.	$\bar{X}$	s.d.	$\bar{X}$	s.d.	$\bar{X}$	s.d.	$\bar{X}$	s.d.	$\bar{X}$	s.d.	$\bar{X}$	s.d.
Age (years)	39.82	9.91	43.60	12.05	44.46	12.63	34.36	8.27	44.29	13.38	42.34	12.51	41.84	12.31
Commute time (min)	25.90	13.13	29.76	20.36	41.64	31.73	28.40	23.44	28.23	22.41	32.65	25.86	35.31	27.90
GDP per capita ($1,000)[2]	38.27	0.00	44.57	0.00	55.56	0.00	62.68	0.00	67.70	0.00	56.56	9.53	54.19	6.43
Unemployment rate (%)[3]	9.20	0.00	3.94	0.00	10.04	0.00	6.10	1.43	4.19	1.23	6.72	2.81	7.47	2.75
General attitudes														
Like large yard	-	-	3.65	1.06	3.79	1.08	3.92	0.89	-	-	-	-	3.78	1.04
Car is a symbol	-	-	2.24	1.05	2.30	1.10	2.90	1.12	-	-	-	-	2.43	1.12
Don't mind being stuck in traffic	-	-	2.01	0.99	1.98	0.97	2.43	1.05	-	-	-	-	2.10	1.01
Travel is wasted time	-	-	2.85	1.06	2.60	1.00	2.90	1.06	-	-	-	-	2.74	1.04
Commute is stressful	-	-	2.68	1.10	2.36	0.98	2.57	1.05	-	-	-	-	2.50	1.04
Categorical variables	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Socio-economic and demographic														
Household income (2018 purchasing power)														
Less than $25,000	5	0.8	30	2.3	158	6.5	67	5.8	125	6.2	385	5.1	255	5.2
$25,000 to $49,999	108	18.0	140	10.6	347	14.4	189	16.4	311	15.3	1,095	14.6	676	13.8
$50,000 to 74,999	0	0.0	268	20.3	493	20.4	438	37.9	355	17.5	1,554	20.7	1,199	24.5
$75,000 to $99,999	192	31.9	245	18.6	470	19.5	165	14.3	327	16.1	1,399	18.6	880	18.0
$100,000 to $149,999	228	37.9	222	16.9	392	16.2	156	13.5	445	22.0	1,443	19.2	770	15.8
$150,000 or more	68	11.3	412	31.3	555	23.0	140	12.1	463	22.9	1,638	21.8	1,107	22.7
Household structure														
Living alone	115	19.1	326	24.8	402	16.6	185	16.0	295	14.6	1,323	17.6	913	18.7
Living with others	486	80.9	991	75.2	2,013	83.4	970	84.0	1,731	85.4	5,191	82.4	3,974	81.3
Gender														
Male	287	47.8	644	48.9	960	39.8	533	46.1	1,001	49.4	3,425	45.6	2,137	43.7
Female	314	52.2	673	51.1	1,455	60.2	622	53.9	1,025	50.6	4,089	54.4	2,750	56.3
Education														
Some high school	0	0.0	5	0.4	3	0.1	12	1.0	22	1.1	42	0.6	20	0.4
Completed high school	15	2.5	70	5.3	66	2.7	106	9.2	134	6.6	391	5.2	242	5.0
Some college	181	30.1	316	24.0	557	23.1	404	35.0	565	27.9	2,023	26.9	1,277	26.1
Bachelor's degree	171	28.5	450	34.2	785	32.5	436	37.7	788	38.9	2,630	35.0	1,671	34.2
Some graduate school	84	14.0	151	11.5	255	10.6	0	0.0	0	0.0	490	6.5	406	8.3
Completed graduate degree	150	25.0	325	24.7	749	31.0	197	17.1	517	25.5	1,938	25.8	1,271	26.0
Occupation														

Manager	-	-	288	21.9	398	16.5	210	18.2	-	-	-	-	8,96	18.3
Other	-	-	1,029	78.1	2,017	83.5	945	81.8	-	-	-	-	3,991	81.7
Travel-related														
Driver license														
Do not have	5	0.8	18	1.4	83	3.4	59	5.1	51	2.5	216	2.9	160	3.3
Have	596	99.2	1,299	98.6	2,332	96.6	1,096	94.9	1,975	97.5	7,298	97.1	4,727	96.7
Physical limitation - transit														
No	-	-	1,277	97.0	2,321	96.1	1,107	95.8	-	-	-	-	4,705	96.3
Yes	-	-	40	3.0	94	3.9	48	4.2	-	-	-	-	182	3.7
Physical limitation - walk														
No	-	-	1,266	96.1	2,251	93.2	1,055	91.3	-	-	-	-	4,572	93.6
Yes	-	-	51	3.9	164	6.8	100	8.7	-	-	-	-	315	6.4
Context-control														
Region indicator														
Northern California[4]	0	0.0	1,317	100.0	2,415	100.0	452	39.1	773	38.1	4,957	66.0	4,184	85.6
Southern California[5]	601	100.0	0	0.0	0	0.0	483	41.8	822	40.6	1,906	25.4	483	9.9
Other California regions	0	0.0	0	0.0	0	0.0	220	19.1	431	21.3	651	8.7	220	4.5
Respondents														
From opinion panel	0	0.0	0	0.0	481	19.9	1,155	100.0	1,211	59.8	2.847	37.9	1,636	33.5
From other sources	601	100.0	1,317	100.0	1,934	80.1	0	0.0	815	40.2	4,667	62.1	3,251	66.5

[1] The ATT subsample includes the 1998, 2011, and 2015 surveys. We use the ATT subsample to develop the attitudinal model in Section 4.2. The ATT subsample has seven extra common variables (five continuous variables and two categorical variables), as shown.

[2] Context-control variable derived from the U.S. Bureau of Economic Analysis (https://www.bea.gov) (state level).

[3] Context-control variable derived from the U.S. Bureau of Labor Statistics (https://www.bls.gov) (county level).

[4] Northern California includes the Sacramento Area Council of Governments (SACOG) and the San Francisco-based Metropolitan Transportation Commission (MTC) regional planning areas.

[5] Southern California includes the Los Angeles-based Southern California Association of Governments (SCAG) and San Diego Association of Governments (SANDAG) regional planning areas.

Table 3. Attitudinal variables common across surveys

Attitudinal variable	Survey	Survey statements
Like large yard	1998	I like to have a large yard at my home.
	2011	I like the idea of living somewhere with large yards and lots of space between homes.
	2015	I like the idea of living somewhere with large yards and lots of space between homes.
Car is a symbol	1998	To me, a car is a status symbol.
	2011	I (would) like to own a car that impresses other people.
	2015	To me, owning a car is a symbol of success.
Don't mind being stuck in traffic	1998	Getting stuck in traffic doesn't bother me too much.
	2011	Getting stuck in traffic doesn't bother me much.
	2015	Getting stuck in traffic does not bother me that much.
Travel is wasted time	1998	Travel time is generally wasted time.
	2011	Time spent traveling is generally wasted time.
	2015	The time I spend commuting is generally wasted time.
Commute is stressful	1998	My commute is a real hassle.
	2011	My commute is stressful.
	2015	My commute is stressful.

4. MODEL ESTIMATION AND ANALYSIS

Two generalized ordered logit models for satisfaction with life are developed and presented here; we note that the first of these models uses the fused dataset across all five surveys, while the second model uses a reduced version of the fused dataset that includes three of the five surveys (1998, 2011, and 2015). The model utilizing all five surveys is described as the *full-sample model*. The full-sample model includes a geographically and chronologically widespread sample, with which we focus on the examination of context variables such as GDP, unemployment rate, and sampling method. The reduced model is described as the *attitudinal model* since it allows an examination of attitudinal variables. The full-sample model maximizes the sample size, while the second model enlarges the set of common variables to include five transport-related attitudinal variables, at the cost of losing two of the five surveys (Table 3). Besides these variables of particular interest (i.e., the contextual and attitudinal variables), we retain demographic characteristics and other travel-related variables in both models.

4.1 Generalized ordered logit model

In this study, satisfaction with life is measured using a five-point Likert-type response scale from "strongly disagree" to "strongly agree". As such, ordinal logit (OL; ordered logit) models would serve this analysis well. However, the dataset used in this analysis violates the parallel lines assumption of OL models, a violation that frequently occurs in practice (Williams, 2006). The parallel lines assumption requires corresponding coefficients (with the exception of the intercept) to be identical across different levels of the dependent variable.

Therefore, we use a less restrictive form of OL, the generalized ordered logit (GOL) model. GOL models relax the parallel lines restriction on the explanatory variables that violate this assumption, while keeping coefficients for the remaining explanatory variables in a parsimonious form (Williams, 2016). We also considered using the multinomial logit (MNL) model, since MNL does not impose the parallel lines assumption across explanatory variables; however, MNL does not take into account the ordinal nature of the dependent variable. Furthermore, in empirical practice, the MNL specification would result in substantially more model coefficients than GOL.

As a result, to balance parsimony, conceptual fidelity, and interpretability, we selected GOL models for use in the analysis presented here. The gologit2 specification in Stata/IC15.1 was used for model development (Williams, 2006).

The GOL model specification can be written as follows:

$$P(Y_i > j) = g\left(\alpha_j, \boldsymbol{X}_i\boldsymbol{\beta}_j\right) = \frac{\exp\left(\alpha_j + \boldsymbol{X}_i\boldsymbol{\beta}_j\right)}{1 + \left\{\exp\left(\alpha_j + \boldsymbol{X}_i\boldsymbol{\beta}_j\right)\right\}} \ , \qquad j = 1, 2, \ldots, M-1 \ , \tag{1}$$

where Y_i represents the life satisfaction of respondent i; α_j is the constant term associated with response j; X_i is a vector of explanatory variables; β_j is the corresponding vector of coefficients associated with response j (some, but not necessarily all, elements of which may be equal across some values of j); and M is the number of life satisfaction categories, which is five in this study; $\alpha_j + X_i\beta_j$ can be interpreted as the observed propensity for life satisfaction to be greater than response j. GOL models are different from OL models in that they allow β_j to vary with j; otherwise, the model specifications for GOL and OL models are identical. The probability of each rating category is:

$$\begin{aligned} &P(Y_i = 1) = 1 - \ g(\alpha_1, \boldsymbol{X}_i\boldsymbol{\beta}_1) \\ &P(Y_i = j) = g\left(\alpha_{j-1}, \boldsymbol{X}_i\boldsymbol{\beta}_{j-1}\right) - g\left(\alpha_j, \boldsymbol{X}_i\boldsymbol{\beta}_j\right) \qquad j = 1, \ldots, M-1 \\ &P(Y_i = M) = g(\alpha_{M-1}, \boldsymbol{X}_i\boldsymbol{\beta}_{M-1}) \ . \end{aligned} \tag{2}$$

From this it can be seen that an increase in $\alpha_1 + \boldsymbol{X}_i\boldsymbol{\beta}_1$ will unequivocally decrease the probability of the lowest life satisfaction response, and an increase in $\alpha_{M-1} + \boldsymbol{X}_i\boldsymbol{\beta}_{M-1}$ will unequivocally increase the probability of the highest response, but the effect of increases in $\alpha_j + \boldsymbol{X}_i\boldsymbol{\beta}_j$ on the middle three responses is ambiguous (Greene, 2018). For this reason, we will interpret variables that have consistent effects across life satisfaction levels (i.e. for which the β_j's are equal across j) in terms of increases or decreases in the *propensity* for life satisfaction, which is unambiguous. For variables that have differing effects across life satisfaction levels (i.e. for which the β_j's vary across j), we will calculate the average marginal effects to illustrate their impact on each life satisfaction response level.

4.2 Full-sample model

The final GOL model developed for this analysis relaxes the parallel lines assumption for household income and the three context-control variables (i.e., GDP per capita, unemployment rate, and the opinion panel indicator), as we found that there are different effects of household income and context-control variables across life satisfaction levels. Table 4 shows the final model results, and indicates that overall, the full-sample model has an acceptable model fit with a ρ^2 (with equally-likely base) of 0.30. We will interpret the explanatory variables found to have significant predictive power for life satisfaction ratings. In addition, Table 5 presents the marginal effects of the explanatory variables whose coefficients have been allowed to relax the parallel line assumption, namely, household income, GDP per capita, unemployment rate, and the opinion panel indicator. Specifically, we present two groups of statistics – actual probability changes and

percentage changes in the probability – since each offers meaningful but different insights in view of the unbalanced shares of the five responses. For example, a large incremental change in probability could represent a small percentage change if the baseline share is large, while conversely, a small incremental change could be a large percentage of a small share.

We look first at household level demographic characteristics. As expected, the model shows that increased household income levels tend to increase the propensity for satisfaction with life. Interestingly, the magnitudes of the coefficients decline as life satisfaction levels increase. This suggests that those with lower life satisfaction tend to have greater returns on their satisfaction propensity as their income levels increase. The trend is consistent with the marginal effects (percentage changes in probability). Specifically, a one-level increase in household income results in larger percentage changes in probability for lower life satisfaction levels than for higher life satisfaction levels. The second household-level variable is household structure, which shows that households with more members have an increased propensity to experience greater satisfaction with life relative to those who live alone. Consistent with countless SWB studies showing the importance of social relationships in general, and close family ties in particular, living with other family members on net brings both practical and emotional support for the burdens of daily life.

Turning now to individual level demographic characteristics, we see that age has a U-shaped relationship with life satisfaction propensity. This indicates that individuals' life satisfaction tends to have a declining trend during their early life stages, with the lowest life satisfaction occurring around the age of 44, on average. After this turning point, people have a greater tendency to be satisfied with their lives. The trend, which is consistent with studies in the literature (Beutel, Glaesmer et al., 2010), is conceptually intuitive, as we can conceive that those in the middle-aged portion of life may have a greater number of stressors – career building, marriages, children, ailing parents – that may result in anxiety and decreased life satisfaction (hence the stereotypical mid-life crisis, e.g., Rosenberg et al. (1999)). Figure 3 intuitively illustrates the average changes in the probabilities of the five response levels as people's age varies from 18 to 93. The probability of strongly agreeing with the life satisfaction statement forms a U-shaped curve across adulthood. In contrast, the probabilities of the other responses do not form such curves due to the restriction that the probabilities of the five response levels sum to one. Still, the figure indicates that people in middle age have the lowest propensity to be highly satisfied with their life and the highest propensity to be less satisfied. In terms of gender, the model indicates that, in general, females tend to have a higher propensity for life satisfaction than males (Welsch and Kuehling, 2017). We see that individuals with higher levels of education tend toward greater life satisfaction. Regarding occupation, we see that those in managerial positions have an increased propensity to be more satisfied with their life relative to those in other occupations.

Regarding transport attributes, we see that increased commute time tends to have a negative effect on life satisfaction. Commuting is a recurring event, often conducted under time pressure and in less-than-pleasant circumstances, which occupies much of an individual's "travel budget" and serves as a spatio-temporal anchor for many other activities. In the U.S., the vast majority of commuting is performed by driving an automobile, and especially for drivers but also for many others, commute time cannot be used as productively as may be desired (Shaw et al., 2019). For these reasons, among others, it is not surprising that longer commutes have a deleterious effect on travel well-being (Smith, 2017) and overall life satisfaction (Hilbrecht et al., 2014).

On the other hand, we also see that having a driver's license has a *positive* effect on life satisfaction propensity. As an instrument of motility (De Vos et al., 2013), license possession can increase one's mobility by providing travel flexibility and an increased radius of potential travel.

As witnessed by the literature on the mobility of the elderly, simply being able to drive can intuitively increase overall life satisfaction (Banister and Bowling, 2004). Thus, we see that commuting specifically has an opposing effect to that of travel freedom generally – probably because of the *lack* of freedom found in much commuting.

The three contextual variables – GDP per capita, unemployment rate, and sampling method – have differing effects across life satisfaction levels. In general, people from regions with a higher GDP per capita are more likely to feel satisfied with life. Also, GDP per capita has the most substantial effects (i.e., the largest positive coefficient) on people who have a high propensity to feel satisfied with life. However, based on the marginal effects shown in Table 5, a one-unit ($1,000) increase in GDP per capita also results in a slight increase in the probability of the lowest life satisfaction level. Interestingly, the unemployment rate positively associates with life satisfaction, i.e., a higher unemployment rate is related to higher life satisfaction. One potential explanation resides in recalling the target group of this study, i.e., employed people. Considering their unemployed peers, people who do not lose their jobs when the unemployment rate is high may be more appreciative of their life than at other times. The marginal effects in Table 5 further show that a one-percentage-point increase in the unemployment rate will result in a probability increase of the medium-high level of life satisfaction ("*Agree*") and probability reductions for the other life satisfaction levels.

In addition to the specific context-control variables of GDP per capita and unemployment rate, we considered including context-control indicators to capture the average impacts of certain unobserved contextual factors. First, we tested using region and year indicators as substitutes for the specific contextual variables in the full-sample model. Compared to using specific contextual variables, the interpretability of the context-control indicators is relatively weak. For example, in the context indicator model, we see that life satisfaction has an increasing trend over the years[2], while people from southern and other California regions have a higher life satisfaction than people from northern California. However, the sources of, or reasons for, these life satisfaction differences are unknown. Further, the fit of the context indicator model is lower than that of the model using specific contextual variables. We also tested including the context-control indicators together with the specific context-control variables; however, the two indicators were insignificant when GDP per capita and the unemployment rate were also in the model.

Regarding the sampling method, online opinion panel respondents tend to have lower life satisfaction propensities relative to respondents recruited using the other sampling methods (mainly address-based sampling). One possible explanation is that the two groups of people have different purposes for survey participation. The online panel respondents are people who previously registered at some websites for survey participation with rewards, while the other sampling methods (mainly address-based sampling) recruit essentially volunteer respondents (even though most of the surveys provided some small incentives). With this in mind, we can see

[2] This result diverges from the literature. For example, Blanchflower and Oswald (2004) report that life satisfaction has been declining for the last quarter of the twentieth century. This may be attributable to a host of reasons. On the one hand, the study reported in this paper captures more recent time periods that are not reported in the literature, i.e., through 2018. On the other hand, differences in sampling method, survey design, and other factors may be contributing to the differences in trends as well. It is also pertinent to note that given the trend of declining survey response rates around the world (National Research Council, 2013; Morton, Cahill and Hartge, 2005), the sample of respondents who are willing to spend time to complete the fairly lengthy, detailed surveys analyzed here may be becoming increasingly less representative with each new cross-section, potentially biased toward having less time pressure, a greater sense of social responsibility,and/ or more positive life attitudes.

that the online panel respondents may have more financial pressure and possibly more ennui, while the volunteer respondents are more likely both to be in a benevolent mood when they started the survey, and to have their sense of well-being further improved by the knowledge of being helpful by completing the survey.

To further analyze the effects of contextual variables, we executed a restricted version of the model with contextual variables removed (Table 4). As we can see, coefficients for the remaining variables do not change dramatically, which demonstrates the model's stability and the independent explanatory power of the two groups of variables. The likelihood ratio test for the removal of a block of variables decisively rejects the null hypothesis that all the contextual variables are irrelevant (χ^2 = 274.88, d.f. = 12, p < 0.001), which indicates the importance of contextual influences in life satisfaction modeling.

Table 4. Full-sample models of life satisfaction

	Generalized ordered logit		*Generalized ordered logit without contextual variables*	
Variable	**Coefficient**	**z-value**	**Coefficient**	**z-value**
Socioeconomic and demographic				
Household income (SD | D)	0.359***	4.71	0.402***	5.35
Household income (D | N)	0.326***	10.44	0.318***	10.44
Household income (N | A)	0.273***	12.84	0.268***	12.90
Household income (A | SA)	0.151***	7.28	0.150***	7.39
Living with others	0.223***	3.64	0.277***	4.60
Age	-0.00210	-1.06	0.00386**	2.03
Age squared	0.000763***	5.84	0.000944***	7.31
Female	0.178***	3.91	0.182***	4.02
Education	0.0860***	3.83	0.0933***	4.90
Travel-related				
Have a driver license	0.358***	2.67	0.377**	2.82
Commute time	-0.00416***	-4.61	-0.00294***	-3.35
Context-control				
GDP per capita (SD | D)	-0.0153	-0.97	-	-
GDP per capita (D | N)	0.0215***	3.51	-	-
GDP per capita (N | A)	0.0199***	4.99	-	-
GDP per capita (A | SA)	0.0487***	13.24	-	-
Unemployment rate (SD | D)	10.548**	2.39	-	-
Unemployment rate (D | N)	6.922***	4.17	-	-
Unemployment rate (N | A)	3.948***	3.61	-	-
Unemployment rate (A | SA)	-1.710	-1.16	-	-
From opinion panel (SD | D)	-0.448	-1.64	-	-
From opinion panel (D | N)	-0.525***	-4.41	-	-
From opinion panel (N | A)	-0.559***	-7.23	-	-
From opinion panel (A | SA)	-0.726***	-10.08	-	-
Thresholds				
Threshold 1 (SD | D)	2.668***	2.59	1.873***	6.50
Threshold 2 (D | N)	-1.081***	-2.72	0.192	1.07
Threshold 3 (N | A)	-1.820***	-6.39	-0.849***	-5.12
Threshold 4 (A | SA)	-5.152***	-17.85	-2.960***	-16.97
Model summary				
Number of cases		7, 514		7,514
Log-likelihood (0)		-12,093.32		-12,093.32
Log-likelihood (thresholds)		-8,853.27		-8,853.27
Log-likelihood ($\hat{\beta}$)		-8,494.77		-8,632.21
ρ^2 (equally-likely base)		0.2976		0.2862

ρ^2 (thresholds-only base)	0.0405	0.0250

*** Coefficient is statistically significant at the 0.01 level.
** Coefficient is statistically significant at the 0.05 level.
* Coefficient is statistically significant at the 0.1 level.
Note: For this sample, the shares of each response are strongly disagree (SD): 1.25%, disagree (D): 6.71%, neutral (N): 13.79%, agree (A): 54.88%, and strongly agree (SA): 23.37%.

Table 5. Average marginal effects of variables with relaxed parallel line assumption in the full-sample model of life satisfaction

		Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Baseline shares		0.0125	0.0671	0.1379	0.5488	0.2337
Household income	Probability change[1]	-0.00438	-0.0187	-0.0209	0.0184	0.0256
	% change in probability[2]	-35%	-29%	-17%	3%	12%
GDP per capita	Probability change[1]	0.000187	-0.00171	-0.00168	-0.00502	0.00823
	% change in probability[2]	1.5%	-2.6%	-1.3%	-0.9%	3.7%
Unemployment rate	Probability change[1]	-0.129	-0.362	-0.145	0.925	-0.289
	% change in probability[2]	-1042%	-566%	-133%	174%	-131%
From opinion panel	Probability change[3]	0.00539	0.0332	0.0547	0.0249	-0.118
	% change in probability[4]	44%	49%	40%	5%	-56%

[1] The probability changes of each response level from a one-unit increase in the explanatory variable. For each explanatory variable, probability changes across the five response levels sum to one.
[2] The proportional changes in the probability of each response level given a one-unit increase in the explanatory variable.
[3] The probability changes associated with belonging to an opinion panel, for each response level. The probability changes across the five response levels sum to one.
[3] The proportional changes in probability associated with belonging to an opinion panel, for each response level.

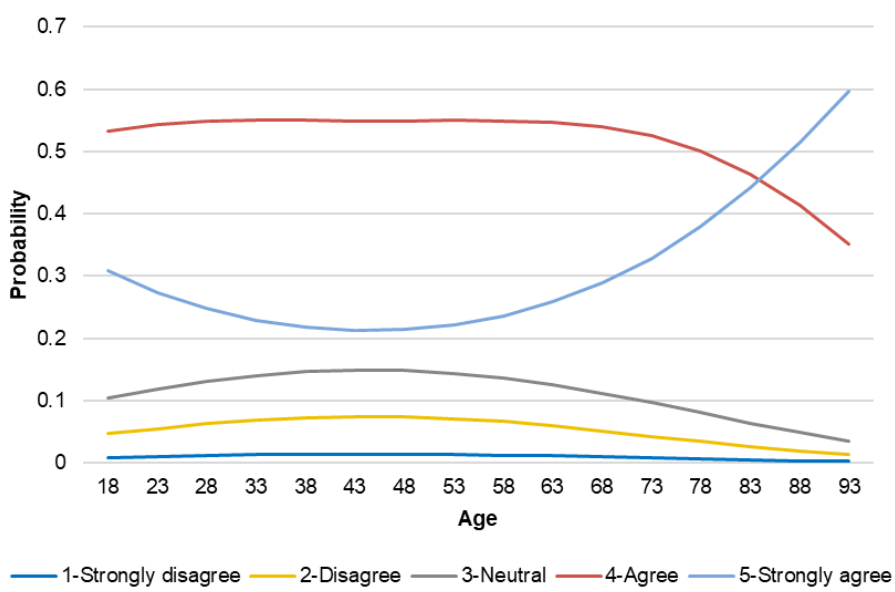


Figure 3. Average changes in the probabilities of different life satisfaction response levels with age

4.3 Attitudinal model

As noted, the attitudinal model (Table 6) is developed using a reduced version of the fused dataset, comprising only three surveys (the 1998, 2011, and 2015 surveys), and thus facilitating the inclusion of a larger set of common variables. To be specific, the attitudinal model includes all explanatory variables used in the full-sample model (as shown in Table 4) as well as seven additional variables that encompass travel-related attributes and attitudes. The attitudinal and full-sample models have similar model results (coefficient and significance) for the shared explanatory variables; accordingly, for economy of presentation, we here focus on interpreting the seven new variables.

Two of the seven additional explanatory variables are travel-related attributes that relate to whether respondents have physical conditions or anxieties that limit their use of transit or walking (i.e., *Physical limitation – transit* and *Physical limitation – walk*). Results indicate that those with physical limitations have lower life satisfaction propensities, likely due to restricted mobility. Further, the physical limitations may also reflect the presence of health problems, which are not directly measured by our surveys but which conceivably have negative effects on life satisfaction. In contrast, having a driver's license, which was only marginally significant in the full-sample model, here has a strongly significant positive effect on life satisfaction.

The five additional explanatory variables are transport-oriented attitudinal statements, which reflect general values as well. The first statement, "*Like large yard,"* captures a residential preference for living in locations that allow large yards and lots of space between homes. This statement is usually associated with a pro-suburban attitudinal factor in prior works (e.g., Kim et al., 2019). The positive coefficient indicates that people who prefer living in suburban areas have increased propensities to be satisfied with their lives. Not surprisingly, the attitudinal result is consistent with the behavioral result; for example, Sander (2011) found that those who live in less urban areas have higher levels of happiness. A possible explanation of the positive relationship between pro-suburban attitudes and life satisfaction is that the suburban life is still an aspiration for many Americans, and may therefore be perceived to offer a more satisfactory living environment. The second attitude, "*car as a symbol"*, reflects the respondent's vanity with respect to owning a car. The results show that respondents who regard cars as status symbols tend to be less satisfied with their lives, perhaps because there will always be others with more status, to whom it is disappointing to compare oneself. Similarly, Olivos, F. et al. (2020) have shown that upward social comparisons have negative effects on life satisfaction.

The last three attitudinal statements ("*Don't mind being stuck in traffic,*" "*Travel is wasted time,*" and "*Commute is stressful*") capture general preferences toward time use, travel liking, and commuting. Those who don't mind being stuck in traffic have increased propensities for life satisfaction, while consistently, those who see travel as a waste or commute as a stress have reduced propensities. These are natural results, especially considering that such attitudes may reflect not only a specific affect toward travel, but also an optimistic/pessimistic outlook on life in general. Note that these attitudes substantially reduce the impact of commute time per se: when attitudes are excluded (as in the second model in Table 6), the coefficient of commute time becomes markedly more negative in compensation, which is not surprising. Nevertheless, even controlling for these attitudes, commute time remains strongly significant.

Thus, we see that the inclusion of these five attitudinal statements allowed for the interpretation of life satisfaction from more dimensions (e.g., personality, time use, travel liking). In Table 6, we also present a model identical to the one discussed here, except with the attitudinal variables removed. Similar to the results for the full-sample model, we note that the remaining

explanatory variables have relatively stable coefficients after the attitudes are removed, and also that the likelihood ratio test for the removal of a block of variables decisively rejects the null hypothesis that all the attitudinal variables are irrelevant (χ^2 = 177.06, d.f. = 5, p < 0.001), which indicates the importance of attitudes in life satisfaction modeling.

Table 6. Attitudinal models of life satisfaction

	Model Specification with Attitudes		*Model Specification without Attitudes*	
Variable	**Coefficient**	**z-value**	**Coefficient**	**z-value**
Socioeconomic and demographic				
Household income (SD | D)	0.442***	3.94	0.421***	3.76
Household income (D | N)	0.306***	7.82	0.282***	7.26
Household income (N | A)	0.270***	9.98	0.242***	9.08
Household income (A | SA)	0.151***	5.62	0.125***	4.74
Living with others	0.144*	1.88	0.211***	2.79
Age	-0.00874***	-3.40	-0.00632*	-2.50
Age squared	0.000772***	4.30	0.000786***	4.42
Female	0.176***	3.03	0.220***	3.82
Education	0.0973***	3.93	0.0796***	3.26
Manager	0.254***	3.40	0.266***	3.58
Travel-related				
Have a driver license	0.496***	3.11	0.381**	2.40
Commute time	-0.00261**	-2.34	-0.00450***	-4.23
Physical limitation – transit	-0.288*	-1.81	-0.375**	-2.36
Physical limitation – walk	-0.375***	-3.02	-0.350***	-2.82
General attitudes				
Like large yard	0.0736***	2.60	-	-
Car is a symbol	-0.0587**	-2.17	-	-
Don't mind being stuck in traffic	0.145***	4.83	-	-
Travel is wasted time	-0.179***	-5.89	-	-
Commute is stressful	-0.196***	-6.18	-	-
Context-control				
Region indicator (base: Northern California[1])				
Southern California[2]	0.0797	0.72	0.0709	0.64
Other California regions	-0.302**	-2.03	-0.274*	-1.86
Unemployment rate (SD | D)	5.817	1.03	7.679	1.36
Unemployment rate (D | N)	9.047***	4.35	10.768***	5.24
Unemployment rate (N | A)	5.063***	3.61	6.728***	4.90
Unemployment rate (A | SA)	4.015***	2.88	5.525***	4.07
From opinion panel	-0.344***	-4.48	-0.362***	-4.82
Thresholds				
Threshold 1 (SD | D)	2.391***	4.02	1.895***	3.34
Threshold 2 (D | N)	0.341	1.06	-0.121	0.45
Threshold 3 (N | A)	-0.503*	-1.74	-0.926***	-4.05
Threshold 4 (A | SA)	-2.845***	-9.43	-3.183***	-13.15
Model summary				
Number of cases		4,887		4,887
Log-likelihood (0)		-7,865.32		-7,865.32
Log-likelihood (thresholds)		-5,572.50		-5,572.50
Log-likelihood ($\hat{\beta}$)		-5,304.59		-5,393.12
ρ^2 (equally-likely base)		0.3256		0.3143
ρ^2 (thresholds-only base)		0.0481		0.0322

*** Coefficient is statistically significant at the 0.01 level.
** Coefficient is statistically significant at the 0.05 level.

[*] Coefficient is statistically significant at the 0.1 level.
Note: For this sample, the shares of each response are strongly disagree (SD): 0.94%, disagree (D): 6.92%, neutral (N): 13.75%, agree (A): 58.13%, and strongly agree (SA): 20.26%.
[1] Northern California includes the Sacramento Area Council of Governments (SACOG) and the San Francisco-based Metropolitan Transportation Commission (MTC) regional planning areas.
[2] Southern California includes the Los Angeles-based Southern California Association of Governments (SCAG) and the San Diego Association of Governments (SANDAG) regional planning areas.

5. DISCUSSION

In this section, we further discuss our research findings and limitations. Firstly, we note that although the life satisfaction models presented have acceptable ρ^2s using the equally likely benchmark (0.2976 and 0.3256), the ρ^2 fit statistics using the thresholds-only benchmark (0.0405 and 0.0481) appear quite low. However, this is a typical outcome when the distribution of responses is unbalanced across the points on the ordinal scale, as is the case here (see Figure 1 and the footnote to Table 4), and does not give a fair picture of the model's explanatory power (Mokhtarian, 2016). Furthermore, even if using the thresholds-only benchmark, this model fit is consistent with life satisfaction models in the literature. For example, ordered logit/probit models usually have a pseudo-R^2 less than 0.05 (Blanchflower and Oswald, 2004; Nie and Sousa-Poza, 2016). Linear regression models usually have R^2 values around 0.2 (Helliwell and Putnam, 2004) and adjusted R^2 values around 0.05 (Hilbrecht et al., 2014; Nikolaev, 2015). It is also notable that many life satisfaction studies do not report model fits, thus precluding the comparison of their overall model performance relative to others in the literature. Low model fits for life satisfaction indicate that there is a sizable range of factors that influence individuals' conscious evaluation of their lives, and at any one time, a typical study is only able to account for a small portion of these explanatory variables (Rojas, 2006). Despite low overall model fits in the satisfaction domain, these models are still able to provide critical insights into the factors that influence life satisfaction across studies.

This study demonstrates the possibility of utilizing diverse cross-sectional surveys in a specific domain to examine factors that influence a variable across time and space, i.e., life satisfaction in this case. However, such an approach inevitably results in shortcomings of the resultant fused dataset. Although we have implemented various approaches to control for the influence of these limitations, we may expect residual problems to remain. For example, through the survey fusion process, we attempted to avoid the influence of different question wordings by systematic question categorization and careful manual selection of common questions. Despite this, we cannot be certain that we have excluded all wording ambiguities that may have influenced responses. Then, to account for the influence of different sampling methods, we used a context-control variable to distinguish different data sources. However, for certain sampling methods, inherent biases are difficult to remove, e.g., the self-selection bias of web surveys (Bethlehem, 2010). In addition, question orders vary across surveys, which may influence respondents' performance on certain questions (Erdogan et al., 2012). Despite these limitations, we believe that the approach shown in this paper can substantially increase the utility of small cross-sectional survey datasets, and thus, can allow for increased contributions to the literature.

6. CONCLUSION

This study develops generalized ordered logit (GOL) models to study the life satisfaction of commuters using a fused dataset of five cross-sectional surveys conducted in California between the years 1992 to 2018. Explanatory variables studied include demographic characteristics, travel-

related attributes, attitudinal variables, and context-control variables. Regarding demographic characteristics, we find that higher income is associated with higher propensities for life satisfaction, but the same income increment has a greater return on satisfaction for less-satisfied groups. In line with previous studies, we see a U-shaped relationship between age and life satisfaction, suggesting that the lowest life satisfaction tends to occur while individuals are in their 40s. We also find that those who are female, more educated, and those who live with others have increased propensities toward higher life satisfaction.

Regarding travel attributes, we see that increased commute time and mobility limitations (e.g., not having a driver's license, physical limitations) are associated with lower life satisfaction propensities. Since the fused survey dataset is multi-year and multi-region, the model uses GDP per capita and the unemployment rate to control for contextual influences. Results show that GDP per capita is positively associated with life satisfaction. Increased unemployment rates are associated with higher life satisfaction, which might be because the study focuses on *employed* people who may feel fortunate compared to their unemployed peers. We also experimented with a substitution model and found that year and region indicators were useful as context-control variables (albeit having lower explanatory power) when specific variables such as GDP per capita and unemployment rate were not available. In this latter (context-control indicator) model, we found an increasing trend of life satisfaction over the years, which might relate to the increasing GDP per capita over the years.

Additionally, we find significantly lower mean life satisfaction for online panel respondents compared to those recruited via more traditional approaches, in support of other studies (Blasius and Brandt, 2010; Fan and Yan, 2010; Szolnoki and Hoffmann, 2013) finding that online panel members are not representative of the general population with respect to a number of variables including attitudes. We also see that attitudes significantly improve the model fit, and aid in understanding the influence of latent characteristics on life satisfaction.

Overall, this study explores the influence of a wide range of variables on life satisfaction, with a focus on contextual variables and transportation-related attributes and attitudes. We hope that this study will serve as a foundation for other researchers in specific domains to explore the approach of fusing multiple survey datasets for the purpose of modeling life satisfaction or other key variables. We especially urge early-career scholars conducting survey-based studies to begin now to consider the possibility of fusing multiple samples in the future, and with an eye to doing so, to give intentional thought to (1) specific questions that could be repeated in multiple surveys, and (2) the need for optimizing uniformity of question and response wording across surveys. Based on our experiences, we recommend the development of a question inventory for common variable selection, as well as the inclusion of relevant context-control variables for models developed using fused datasets.

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