Traffic measure package configurational impact on behavioral policy measures

A 'Beter Benutten Vervolg' case study

Martijn van Kalmthout

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Colophon

Author

Martijn van Kalmthout
Delft University of Technology
Faculty of Civil Engineering and Geoscience
Master student Transport & Planning

Graduation committee

Prof.dr.ir S.P. Hoogendoorn
Chairman
Delft University of Technology
Faculty of Civil Engineering and Geoscience
Department of Transport & Planning

Dr.ir. A.J. Pel
Daily supervisor
Delft University of Technology
Faculty of Civil Engineering and Geoscience
Department of Transport & Planning

Dr. J. A. Annema
Delft University of Technology
Faculty of Technology, Policy and Management
Department of Engineering Systems and Services

Date: May 22, 2020

Preface

The document that lies before you is the thesis: “Traffic measure package configurational impact on behavioral policy measures”. The research of this study is predominately based on a data analysis of behavioral policy measures from the ‘Beter Benutten Vervolg’ program. This thesis was written to complete the Master programme Transport and Planning at the faculty Civil Engineering of the Delft University of Technology.

This research lasted from February 2018 until May 2020. The research was started at the request of Ecorys, where I took an internship and where I spent my time at the beginning of this research. After a difficult time being away from this research I finished this it independent from Ecorys.

I would like to thank all of the members from my graduation committee. This being the chairman Prof.dr.ir Serge, Hoogendoorn, my daily supervisor Dr.ir. Adam Pel and Dr. Jan Anne Annema.

Most of all I would like to thank Dr.ir. Adam Pel, for helping me restart my thesis after being away for a while and all the guidance and pleasant talks along the way. I would also like to thank Bregtje Bax who helped me during my time at Ecorys. Whom I could always exchange ideas with.

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Summary

The impact of the traffic measure package (TMP) configuration on performance outputs of a behavioral policy measure (BPM) is in practice predominately estimated, but not yet substantiated. This was also the case for TMPs implemented in 'Beter Benutten Vervolg' (BBV), which was a program that executed hundreds of policy measures to get car users to avoid peak. These policy measures were executed in multiple regions throughout the Netherlands. After the completion of BBV, a large dataset, consisting of the implemented BPMs remained. This gave the opportunity to analyze this dataset and gain insight into interaction impacts between policy measures in TMPs. That insight is helpful for decisionmakers who construct TMPs containing BPMs. The goal is that the knowledge about the impact of TMP configuration on the performance outputs of BPMs will lead to better performing BPMs in future implemented TMPs.

The research methods for this study included a literature study, a practical knowledge study, a travel behavior questionnaire analysis and a data analysis of BPM data from BBV. The literature study consisted mainly of international research papers on the topic. The practical knowledge study was based on the evaluation of BBV. The insights gained from both studies led to the formation hypotheses on a TMP configuration that could positively impact the performance outputs from a BMP within that package. These hypotheses were then tested using both the travel behavior questionnaire data and the BPM data from BBV. Two different performance outputs of a BPM are tested by these data analyses. The travel behavior questionnaire data analysis tackled the degree of participation of a BPM. The BPM data analysis tackled the activity of a BPM, in this analysis the BPMs are compared on multiple observation levels. These two performance outputs of a BPM together describe the total effectiveness of that BPM.

The hypothesis coming from the literature study was: when a BPM aimed to incentivize car users to switch to an alternate mode, interacts with an IPM aimed to incentivize car users to switch to the same alternate mode, this BPM will have higher performance outputs compared to when this BPM would not be linked to such an IPM. The hypothesis coming from the practical knowledge study was: when a BPM aimed to incentivize car users to switch to an alternate mode, interacts with another BPM aimed to incentivize car users to switch to a different alternate mode, this BPMs would have higher performance outputs than when they are not linked to such a BPM.

The findings from the travel behavior questionnaire data analysis, concerning the first hypothesis, were that when infrastructural improvements are linked to a behavioral improvement of alternative travel possibilities an additional number of car users is persuaded to reduce their car use. These car users could only be persuaded to reduce their car use due to both of these improvements being implemented. This would mean that when a BPM interacts with an IPM incentivizing car users to switch to the same alternate mode, this BPM would attract more participants and would therefore have a higher degree of participation than when this BPM would not be linked to such an IPM. The findings from the travel behavior questionnaire data analysis concerning the second hypothesis were that when improvements of bicycle travel possibilities are linked with improvements of public transport travel possibilities, only 10.9% of car users need both of these improvements to reduce their car use. Because there is a low percentage of overlap in car users that need both modes improved to reduce their car use, these types of BPMs would attract less participants. The BPMs essentially steal participants from each other, making the degree of participation lower than when these types of BPMs do not interact.

The findings from the BPM data analysis concerning the first hypothesis were that the BPMs that interact with IPMs had a possible higher activity, over some observation levels, than those without that link. There was however no statistically significant outcome on having that higher activity across other observation levels. Overall, this means that it is could be possible that this interaction would lead to a higher activity from participants. The findings from the BPM data analysis concerning the second hypothesis were that the BPMs that interact with BPMs with the incentive to switch to another mode had a probable higher activity than those without that link. This was true over most observation levels. Only on the observation level with the comparison of to the expected average activity, based on the region in which the BPMs were implemented, no statistically significant outcome arose on that type of interaction leading to a higher activity. Overall, this means that it is probable that this link would lead to a higher activity from participants. When performing a regression analysis on the impact of TMP configuration, measure type and region, on the activity of a BPM, the TMP configuration seemed to have the largest impact. Besides having the largest impact the TMP configuration also had the highest predictive accuracy. This makes the TMP configuration an important component of the success, measured in activity, of a BPM.

The results of this study led to two main policy implications.

- Accompany a BPM with an infrastructural improvement that incentivizes the switch to the same mode

Car users would be more likely to participate in that BPM and when they participate there is an indication that the activity in avoiding peak is also higher. Both of these performance outputs being positively impacted would also lead to a higher effectiveness of this BPM.

- Offering multiple options for the car users to avoid peak

Less car users would probably participate in such a BPM. The car users that do participate probably have a higher activity in avoiding peak. It is still unclear if how the effectiveness of such a BPM is impacted.

Other policy implications based on this study include knowing the target audience, knowing the transportation network and the monitoring of the implemented policy measures. When packaging policy measures it is important to know the target audience. A TMP can be better tailored to a target audience if there is more information about that target audience. In that way the TMP can comply to the needs of that specific audience. While it is great to know more about the target audience, the transport network needs to be examined as well. This is to see if car users are actually able or likely to switch to alternate modes or chose another route. Combining the knowledge on the target audience and the transportation network can lead to the best fitting TMP. Monitoring the number of reached target audience, the number of participants and the number of peak avoidances, would give a complete image of the performance of a policy measure. When this is monitored the same way throughout multiple projects, this can then be used for an in-depth evaluation of policy measures.

This study also provided some leads for further research. These leads are: performing dedicated policy measure studies, studying contextual characteristics and studying more performance outputs. When performing dedicated policy measure studies, the research questions are known beforehand, making it possible to tailor the context in such a way that there is less noise in the dataset from outside factors. This was not the case in this study, because the dataset was not compiled with the research questions of this study in mind. When studying the TMP configurational impact it also became clear that there are a lot of outside factors of impact on the performance of a BPM. There is still a lot to be learned about the impact of these factors. Studying other impacting factors on the performance of policy measures would also be a good path to continue research on. Connecting to the policy implication of monitoring multiple performance outputs for a policy measures, further research can also be done on other performance outputs and/or multiple performance outputs of a policy measure. This would give a better image of the workings of a policy measure, which is very useful for decision makers implementing policy measures in future projects.

Contents

1 Introduction

This study is on behavioral policy measures in traffic measure packages, implemented to get car users to avoid driving during peak hours. The study focusses on the impact of traffic measure package configuration on the performance outputs of behavioral policy measures, within these traffic measure packages. The opportunity to perform this study arose due to the availability of policy measure data from the 'Beter Benutten Vervolg' program. 'Beter Benutten Vervolg' is a nation-wide program containing hundreds of policy measures to get car users to avoid driving during peak hours. In this program a large variety of policy measures was implemented. These policy measures were executed separately and simultaneously in traffic measure packages.

1.1 Research objective

1.1.1 Research problem

The research problem lies in getting a grip on how the performance outputs of a behavioral policy measure (BPM) are impacted by interacting with other behavioral and/or infrastructural policy measures (IPM). This interaction can occur when they are executed together in a traffic measure package (TMP). This topic was chosen as the research problem because still little is known about the interaction impact of policy measures on each other within TMPs, despite TMPs being commonly implemented to solve traffic problems. This topic is therefore also a knowledge gap. The choice was made to study BPMs instead of all policy measures, due to these having the most usable performance outputs available from the BPMs in the to be studied dataset from 'Beter Benutten Vervolg' (BBV).

To illustrate the knowledge gap in practice, section 4.2 contains examples of how the interaction impact between policy measures in TMPs was estimated in BBV. The elaboration of what BBV precisely entailed is also presented in this chapter. Illustrated cases in section 4.2 show that the regions participating in BBV did put some thought in the impact of performing multiple policy measures at once on the total effect on peak avoidances of the TMP. Although the fact that these were rough estimations and not substantiated by previous studies means that there was still a gap in practical knowledge on this particular topic. This knowledge gap is precisely the reason why this is the focus of this study. The knowledge of interaction impact on performance outputs of BPMs could help when estimating the performance outputs of BPMs in TMPs in similar future projects.

In literature, there are some studies connecting to the research topic of TMP configurational impact on policy measures. The papers of these studies are discussed in chapter 3, where a literature study is performed. The papers that are part of the literature study suggest that there are interaction impacts on the performance outputs of policy measures. The claims from these papers are substantiated with data from their own or other studies on this topic. To the author's knowledge however, no study has been performed on the TMP configurational impacts on performance outputs of BPMs based on data from such a large scale, as the dataset obtained from BBV. This dataset consists of BPMs that were implemented in a nation-wide Dutch program during the span of 2 years. Performing an analysis on a real-life dataset from such a large scale is a gap in science. Having this data available is also the reason why this study was performed. The goal is to get a grip on the impact of TMP configuration on the performance outputs of a BPM inside this TMP. A better understanding of these impacts can help decision makers, who compose TMPs, in the future which types of TMP configurations are beneficial to implement and which are not.

1.1.2 Main research question

Having the research problem being the TMP configurational impacts on the performance outputs BPMs from that TMP, leads to the following main research question:

How does a traffic measure package configuration impact the performance outputs of a behavioral policy measure in that traffic measure package?

1.1.3 Sub-questions

To support the main research question, a few sub-questions are set up. The sub-questions are as follows:

1. When are policy measures interacting with each other?
2. Which other factors impact performance outputs of policy measures?
3. What is already known about the impact of policy measure interaction?
4. What is a fair method of analyzing traffic measure configuration impact, with multiple different impacting factors present?
5. How is the degree of participation affected when a car user is influenced by multiple policy measures?
6. How is the activity affected when a car user is influenced by multiple policy measures?
7. How is the effectiveness affected when a car user is influenced by multiple policy measures?
8. Which traffic measure package configuration positively impacts the performance outputs of a behavioral policy measure?

1.1.4 Scope

The goal of this study is to find the impact of the TMP configuration on the performance outputs of BPMs within those packages. Reaching that goal means that the performance outputs of BPMs from different TMP configurations need to be analyzed. The search therefore is to find the right approach to compare between the performance outputs of BPMs, where it is possible to analyze the impact of the TMP configuration.

Type of policy measures to be studied

In this study the performance outputs of BPMs will be analyzed. There were however also IPMs implemented in BBV. The performance outputs of IPMs are not analyzed in this study and IPMs are considered supportive to BPMs when the switch to the same alternative mode is incentivized. IPMs are considered supportive to BPMs because they give extra incentives to change the behavior of car users. They can do that by for instance providing different travel routes or increasing the robustness of the cycling network. The assumption to treat IPMs supportive to BPMs and not analyze their performance outputs was made due to the difficult nature of pinpointing the group of car users that use this changed infrastructure for their peak avoidance. This led to having very few data available on the performance outputs of IPMs in BBV. The lack of data from IPMs made it impossible to come to statistically significant outcomes when analyzing the performance outputs of IPMs.

In this study the assumption to treat IPMs as being supportive to BPMs is constructed as follows. When a car user from a certain area is taking part in a BPM and an IPM is also present in that same area during the same time period, this car user is also considered to be influenced by that IPM. This because all car users in that area could use that changed infrastructure. This then holds that when a BPM is implemented in the same area during the same time period, the IPM is always interacting with the BPM.

Performance outputs of a BPM to be studied

The BPMs will be analyzed based on their performance outputs. The performance outputs that are used are: the degree of participation, the activity and the effectiveness. The performance outputs are explained by the elaboration of the workings of policy measures.

Workings of an independent policy measure

A policy measure can have a few different outputs before eventually reaching the outcome, which in most cases is the number of peak avoidances. To come to peak avoidances first there needs to have been a target audience and participants belonging to that policy measure. The outputs, the outcome and factors between the these are illustrated in Figure 1. The outputs are and outcome are presented in a black box. The performance outputs are shown with blue arrows.

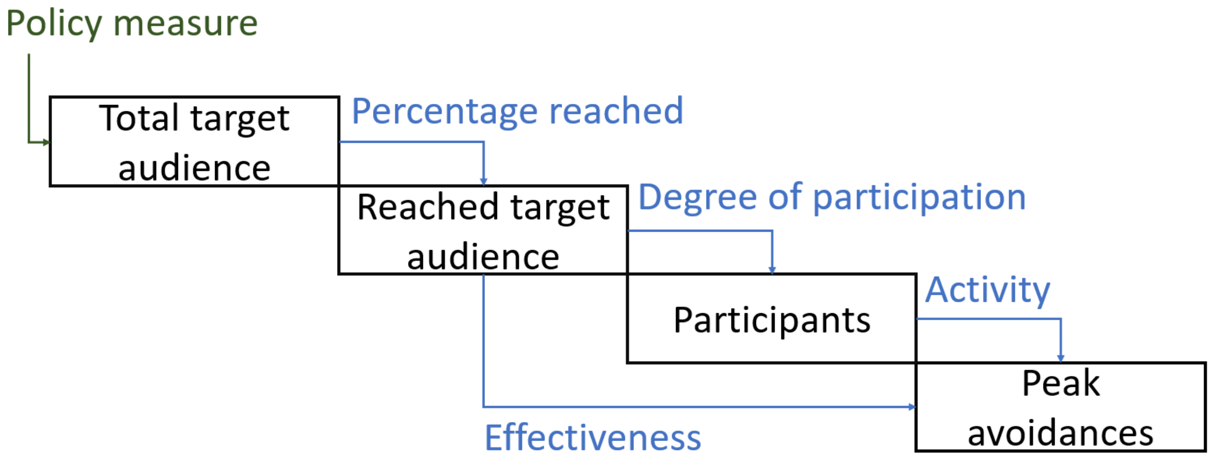

Figure 1 – Waterfall diagram, (performance) outputs of a policy measure

A policy measure has a total target audience that consists of car users that cause hindrance over a certain bottleneck during a certain time period, or from a certain time period in a general area. A share of the total target audience will be reached by the implemented policy measure. This share can be called the reached target audience. These car users can for instance be reached by a policy measure by getting a letter from the government, by a general marketing campaign or by their employer. This group of car users is considered to be influenced by the policy measure, due to their exposure to that policy measure and being part of the total target audience. The share of car users that then chose to participate in the policy measure can be described as the degree of participation.

Degree of participation:

$$Degree\ of\ participation = \frac{Participants}{Reached\ target\ audience}$$

When dividing the number of participants by the size of the reached target audience, the degree of participation can be calculated. This will be the share of the car users that is reached by the policy measure and is taking part in the policy measure as well. This essentially embodies the initial 'attractivity' of a measure i.e. how willing are car users to participate in a policy measure.

Being a participant means that all car users in this group are avoiding peak due to the implemented policy measure at least once. Next, to come to the number of peak avoidances, the participants induce a certain number of peak avoidances per unit of time. This can be described as the activity of the participants.

Activity:

$$Activity = \frac{Peak\ avoidances}{Participants}$$

When dividing the number of peak avoidances per unit of time by the number of participants, the number of peak avoidances that an average participant provides per unit of time can be calculated. This embodies the attractivity to keep using the policy measure by the participants i.e. the willingness of the participants to keep avoiding peak during active period of that policy measure. The unit of time will be expressed in days, conform the output of the BBV program.

The effectiveness of a policy measure can then also be determined. This is the number of peak avoidances that are provided by all car users that are influenced by that policy measure.

Effectiveness:

$$Effectiveness = \frac{Peak\ avoidances}{Reached\ target\ audience}$$

When dividing the number of peak avoidances per unit of time, by the size of the reached target audience, the number of peak avoidances that an average reached car user provides can be calculated. This essentially embodies the effectiveness of a policy measure on the reached target audience i.e. the willingness to participate in a policy measure and to keep avoiding peak during active policy measure period. The unit of time will be expressed in days, conform the output of the BBV program. Note that the effectiveness is the multiplication of the degree of participation with the activity.

Workings of interacting policy measures

Above the workings of an independent policy measure are explained, including the different outputs to eventually reach peak avoidances. These workings are similar when multiple independent policy measures are implemented. When policy measures are independent, they reach a different target audience or are implemented at different periods. They therefore reach their peak avoidances from their own independent paths, which results in them working the same as a standalone policy measure. When policy measures are of interacting with other, they reach the same group of car users from the target audience at the same period. The degree of participation, the activity and the effectiveness can now be impacted by the interaction between these interacting policy measures. To interact with each other, the policy measures should influence same the group of car users in the reached target audience, this should therefore overlap between the two policy measures.

The degree of participation is impacted between interacting policy measures. Here the car users from the reached target audience have now the choice to participate in none, one or both policy measures, instead of participating or not with an independent policy measure. This is excluding the scenario when it is prohibited to participate in multiple policy measures. This difference in choice impacts the individual degree of participation for the interacting policy measures as well as the fact that to come to participants the same group of car users is reached. When looking at the activity, this still works the same as it does for independent policy measures, the peak avoidances are only generated by the participants from that policy measure. The only difference is that the participants had the ability to choose between policy measures to become a participant in the case of interacting policy measures, compared to not having that choice in an independent or separately implemented policy measure. The total effectiveness for a interacting policy measure is still the multiplication of the degree of participation and the activity.

The interest in the workings of interacting policy measures, lies in the fact that the three above named performance outputs can be different from independent policy measures, due to the impact of TMP configuration. This is what is studied in this research.

Contextual characteristics impacting performance outputs of a BPM

Besides the TMP configuration there are other factors that impact the performance outputs of a BPM. In this study these other factors are described as contextual characteristics of a BPM. They can be categorized into two groups: regional characteristics and organizational characteristics. The regional characteristics describe the traffic system and the socio-demographic characteristics from the region in which the BPM is implemented. The organizational characteristics describe the process of executing a BPM. The impact of certain regional characteristics from the traffic system are being analyzed quantitively in section 9.4.3, in the appendix. The organizational and the socio-demographic characteristics will not be analyzed quantitively. When analyzing the impact of TMP configuration on the performance outputs of a BPM, the impact of these contextual characteristics will be taken into account and will be discussed qualitatively.

1.2 Contribution

The main contribution will be the insight into the impact of TMP configuration on the performance outputs of BPMs. Although there are already some estimates on case-to-case basis in practice, see section 4.2 and there is some literature on the topic, see section 3.2, no study has been performed on real-life data on a nation-wide scale (The Netherlands). The availability of such a large dataset makes this study unique. To be specific, from the dataset from BBV only the activity of BPMs can be analyzed. The degree of participation will be analyzed using an independent dataset, from the same time period in the Netherlands. Together these datasets will give a more complete insight into the total performance of BPMs, while being impacted by TPM configuration.

The contribution of gaining insight into the impact of TMP configuration on the performance outputs of BPMs can help decision makers make more efficient choices when composing TMPs in the future. A better understanding of how the interaction within a TMP works will help when composing a TMP. The information if a TMP configuration would be beneficial or detrimental to the performance outputs of the BPMs in that TMP can be very useful.

The framework that is used to see if policy measures interact with each other and the method of analyzing these policy measures is part of the contribution as well. A similar framework can be used in future research to examine other impacting factors, such as regional- and organizational characteristics, on performance outputs of policy measures. The same holds for other performance outputs of policy measures, such as the degree of participation and the effectiveness. These can also be analyzed using the same framework.

1.3 Outline

The outline of this thesis is as follows. In chapter 2 the research method that is used in this study is explained. This will consist of the reasoning why these methods are chosen and how these methods are implemented. In chapter 3 the literature study is performed. Topics of the literature study are: factors that impact policy measures and reasoning why TMPs are implemented over separate policy measures. The main findings of the literature study then lead to an hypothesis on TMP configuration that could positively impact the performance outputs of a BPM. Chapter 4 will be a study of the practical knowledge on the topic. This is done by studying the evaluation surrounding BBV. The knowledge before and after the program will be elaborated. Here the main findings also lead to an hypothesis on TMP configuration that could positively impact the performance outputs of a BPM. Chapter 5 will then be the analysis of pre-existing travel behavior questionnaire data. Here the impact of improvements in bicycle and public transport travel combinations on car use reduction are analyzed. This is done to gain insight into the impact of the TMP configurational hypotheses on the degree of participation of a BPM. In chapter 6 the BPM data from BBV will be analyzed. Here the TMP configurational hypotheses on the impact on the activity of a BPM are analyzed. The impact of the region and the measure category are analyzed here as well. Lastly, in chapter 7 the main findings are elaborated together with a discussion on this study, the policy implications of the conclusions and opportunities for further research.

2 Research methods

In this chapter the research methods of this study will be explained. The research methods consists of the tools which are used to answer the research questions. The research methods of this study are: performing a literature study, obtaining practical lessons from BBV, the analysis of travel behavior questionnaire data and the analysis of BPM data obtained from BBV. Table 1 gives an overview of the connection between the research methods and the research questions. In this table all of the research questions are shown together with the research methods that are used to answer these questions. To complete this overview, the chapters in which the research question is will be elaborated are added as well.

Table 1 - Connection between the research question and the research methods

Nr.	Research questions	Research method	Chapter
1	When are policy measures interacting with each other?	-	2
2	Which other factors impact performance outputs of policy measures?	Literature study	3
3	What is already known about the impact of policy measure interaction?	Literature study & practical knowledge study	3 & 4
4	What is a fair method of analyzing traffic measure configuration impact, with multiple different impacting factors present?	-	2
5	How is the degree of participation affected when a car user is influenced by multiple policy measures?	Travel behavior questionnaire data analysis	5
6	How is the activity affected when a car user is influenced by multiple policy measures?	BPM data analysis	6
7	How is the effectiveness affected when a car user is influenced by multiple policy measures?	Travel behavior questionnaire & BPM data analysis	7
8	Which traffic measure package configuration positively impacts the performance outputs of a behavioral policy measure?	Travel behavior questionnaire & BPM data analysis	5, 6 & 7
Main	How does a traffic measure package configuration impact the performance outputs of a behavioral policy measure in that traffic measure package?	Travel behavior questionnaire & BPM data analysis	5, 6 & 7

2.1 Literature study

To find out what is already known about the impact of policy measure interaction and which other factors are impacting policy measures, the literature study is performed. This literature study will be the base of this research. The literature study is predominately based on research papers. The answers to the sub-questions tackled by the literature study will give insight into possible impacting TMP configurations on the performance of a policy measure. This insight will lead to a hypothesis on a specific TMP configuration which could positively impact the performance outputs of a policy measure. This hypothesis can be tested by performing an analysis on travel behavior questionnaire data and BPM data from BBV. These two data analysis methods are elaborated in section 2.3 and 2.4.

The literature study is also used to gain insight into other factors that could impact the performance outputs of a policy measure. This information is useful to make a fair analysis on the impact of TMP configuration, while keeping in mind other impacting factors.

2.2 Practical knowledge study (lessons learned from BBV)

Next to gaining knowledge on the impact of policy measure interaction from a research standpoint, the practical side of this topic is studied as well. This is done by studying the lessons that are learned surrounding the BBV program. The knowledge before starting BBV will give insight into what was already known about the topic and what was still unknown. The part of the topic that was still unknown elaborates the knowledge gap of the studied topic. Studying the practical lessons from the evaluation of BBV will give insight into the practical side of the to be studied topic. Similar to the literature study will this information lead to a hypothesis on a TMP configuration which could positively impact the performance outputs of a policy measure. This hypothesis can be tested by performing an analysis on travel behavior questionnaire data and BPM data from BBV. These two data analysis methods are elaborated in section 2.3 and 2.4.

2.3 Travel behavior questionnaire data analysis

To get a view of the impact of TMP configuration on the degree of participation of a BPM, travel behavior questionnaire data is analyzed. The data is from ‘Gedragsmeting Beter Benutten 2017’, which was a revealed preference survey on travel behavior held among Dutch citizens. The part of the dataset that is used contains car users that have reduced their car use based on the improved possibilities to travel by bicycle and public transport. To recap, Figure 2, shows the degree of participation within the waterfall scheme of performance outputs of a policy measure.

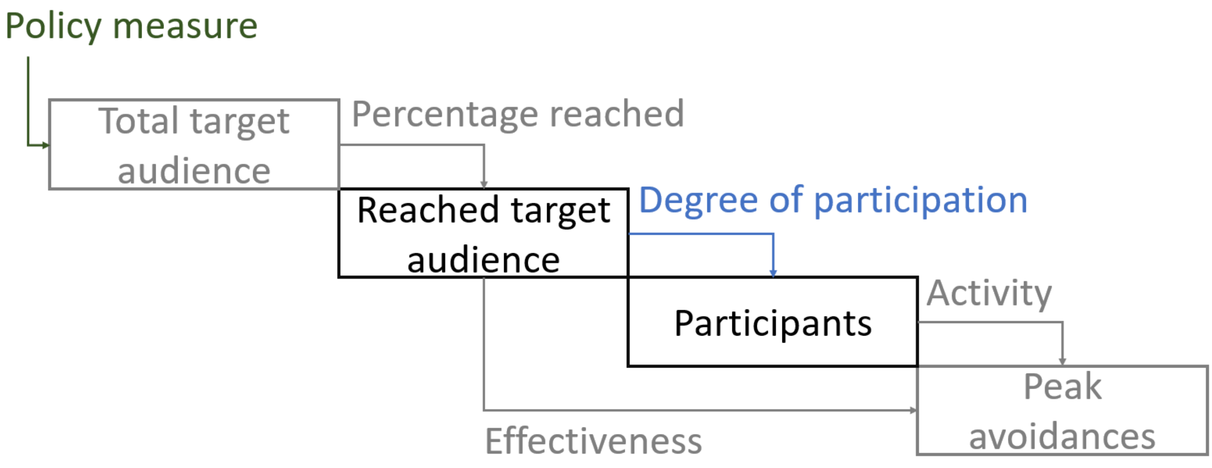

Figure 2 – Waterfall diagram, degree of participation of a policy measure

This dataset is used to describe the degree of participation of a BPM. This dataset is used to describe that aspect of a policy measure due to it not being possible to analyze this by using the dataset from BBV. The questionnaire dataset is independent from the BBV dataset. Similar as for the BBV dataset is the questionnaire dataset used to give insight into the TMP configurational impact on BPMs. The TMP configurations that are analyzed are based on the hypotheses that are formed in the literature study and the practical lessons from BBV.

In this dataset car use reduction is linked to behavioral and infrastructural improvements in bicycle and public transport travel possibilities. Combinations of these improvements are analyzed to gain insight into how car users are persuaded to reduce their car use while being influenced by combinations of improvements.

2.3.1 Data choice justification (travel behavior questionnaire data)

When starting this study it was thought that the policy measure dataset coming from BBV would be enough to analyze the TMP configurational impact on all three before mentioned performance outputs (degree of participation, activity and effectiveness). An analysis of the degree of participation and the effectiveness of a policy measure was however not possible using the BBV dataset, because a lack of reported reached target audience for the BPMs in this dataset. Only being able to analyze the impact of TMP configuration on the activity of a BPM would not give a complete view of the actual impact on the performance outputs as a whole. The choice was therefore made to complete that view with another dataset. The analysis of this travel behavior questionnaire could fill the gap of the missing degree of participation component. The degree of participation and the activity together make up the effectiveness, to make the image complete.

There is however a consideration to be had on using different datasets. The datasets are not coming from the same source, but are both based on Dutch travels in the same time period, making both datasets a pretty good match. This is because the goal of performing the questionnaire was to gain knowledge about the Dutch travel behavior to help form policy measures in BBV. The up- and downsides of using this dataset for this study are listed in Table 2 and elaborated below.

Table 2 - Up- and downsides of using the questionnaire dataset

Upside	**Downside**
Large dataset	Not executed for this study
Gives a more complete image	Datasets are from different sources

The first upside of using this dataset is that it includes a substantially large group of Dutch car users. Both questions that are used in the analysis had hundreds of respondents. It would not have been possible to gather such a large dataset specific for this study. The second upside of using this dataset is that more of a complete image of the impact of TMP configuration on the performance outputs of BPMs will be formed. Otherwise only the activity could be analyzed. This would only give leave an incomplete image.

The first downside of using this dataset is that it was not compiled with the research questions of this study in mind. This means that it does not translate one-to-one into answering the research questions, making it that some assumptions are required when using this dataset to answer the research questions. Having to add these assumptions brings a level of uncertainty when coming to conclusions to these research questions. The second downside of using this dataset is that it is different from the dataset from BBV. Having the datasets be different means that the conclusions that are obtained from analyzing both dataset cannot straightforward be added together. Combining the conclusions from two different datasets also brings a level of uncertainty to the conclusions.

The choice was made to use both datasets in this study, because the benefit of a more complete image was considered more valuable to decisionmakers than the downside of more uncertainties in the conclusions.

2.4 BPM data analysis

To get a view of the impact of TMP configurations on the activity of a BPM, policy measure data from BBV is analyzed. This dataset contains BPMs from different TMP configurations and their corresponding activity. To recap, Figure 3 shows the activity within the waterfall scheme of performance outputs of a policy measure. The dataset from BBV contains 51 BPMs, with a recorded activity of participants. The degree of participation and the effectiveness are not present in that dataset, due to a lack of data from the reached target audience for those BPMs.

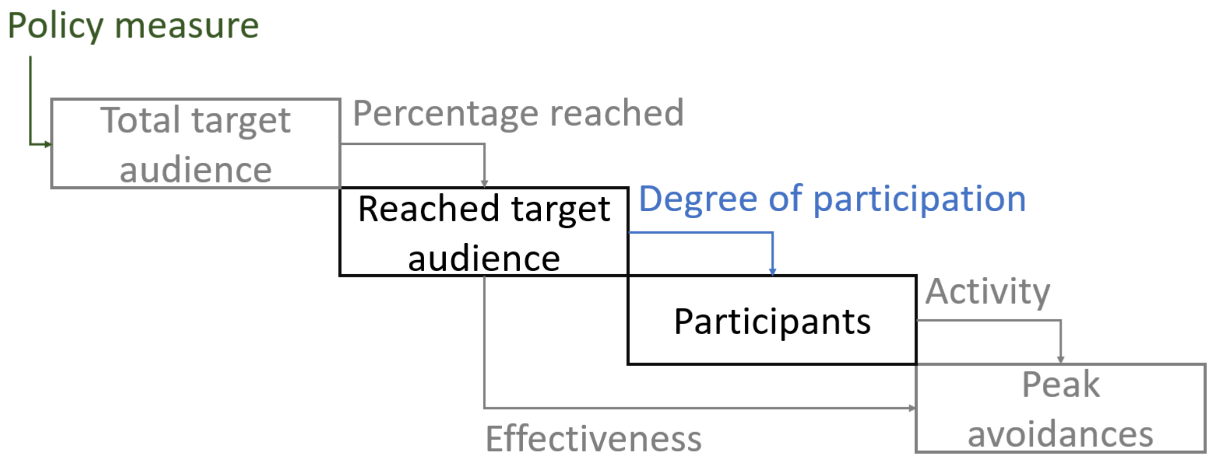

Figure 3 - Waterfall diagram, activity of a policy measure

Same as for the travel behavior questionnaire dataset the dataset from BBV is used to test the hypotheses that are formed in the literature study and the practical lessons from BBV.

2.4.1 Data choice justification (BPM data obtained from BBV)

The choice to use this dataset in the study is based on the availability of this dataset. Having a dataset available with information from such a large number of policy measures all implemented during the same short time period in the same country was a chance that could not be passed up. This is also the largest upside of using this dataset. It consists of a large number of policy measures that have been implemented in a real-life situation, making it a very good representation of performance outputs of the BPMs during that time period in the Netherlands. Such a large dataset could not have been obtained specific for this study. The downside of using this dataset for this study is that it was not created with the specific research questions from this study in mind. This means that there are a lot more factors of impact on the activity of BPMs than the TMP configuration. These other factors could be made similar in a test situation. All these other factors being of impact makes the analysis of the activity of the BPMs not straightforward. This means that there is some uncertainty when coming to conclusions about the impact of TMP configuration on the activity of BPMs. Nevertheless, the availability of such a large dataset representing a specific time period in the Netherlands outweighs the level of uncertainty in forming conclusions. Therefore the choice was made to use this dataset for this study.

2.4.2 Preparing the BPM dataset for the analysis

The dataset consist of policy measures implemented in the BBV program with their descriptive attributes and outputs. This dataset was drawn up using monitoring and evaluation data. The data from the individual policy measures came from the respective regions that implemented these, due to the regions being responsible for the monitoring and outputs of the policy measures. In practice, this means that they outsourced this to a consultancy. The outputs were then evaluated on plausibility by Ecorys. This evaluation was only done for policy measures in packages of a medium or large size (quantified based on estimated ex-ante peak avoidances). The final reports of the regions, on the implemented policy measures, contain the outputs of those measures. The final reports were also checked on plausibility by a monitoring team of I&W. Due to the data being checked by impartial parties and the outputs being substantiated by underlying reports, which were also checked, the values of these outputs are considered to be plausible.

A sample of the usable information from the initial dataset is shown in Table 3. For a complete overview, the dataset as a whole is shown in Table 31 which is in section 9.1 of the appendix. The code, name of the measure, name of the sub-measure, number of reached target audience, number of participants and number of peak avoidances are all usable information about that policy measure. The code gives each policy measure their unique number and also includes the region in which this policy measure is implemented. The name of the measure and sub-measure together with the measure category give an indication of what that policy measure entailed. The number of reached target audience, number of participants and number of peak avoidances give an indication about the performance of that policy measure.

Table 3 – Sample of the initial BPM dataset from BBV

Code	Name measure	Name sub-measure	Measure category	Reached target audience	Participants	Peak avoidances
HGL-BBV-001a	Projecten	KNMP	Bicycle demand	-	68	65
HGL-BBV-001b	Projecten	DB+	Bicycle demand	-	35	8
HGL-BBV-001d	Projecten	E-biketool	Bicycle demand	-	111	19
LWD-BBV-002b	Leeuwarden op de fiets	Rij2op5	Bicycle demand	7095	1490	158

To be able to perform the data analysis of the impact of TMP configuration on the activity of a BPM, a few steps need to be taken to prepare the initial dataset. To test the impact of TMP configuration, it should be known if a BPM interacted with another policy measure and if so, what the TMP configuration looked like. It is therefore necessary add to the dataset which policy measures interacted with each other. Based on a traveler point of view, for policy measures to interact with each other, the same group of car users should be influenced by both policy measures. This is the case when there is an overlap in reached target audience and period in which the policy measures were active. It is assumed that when there is overlap between these criteria the same group of car users is influenced by both measures. When this is not the case and policy measures are influencing different groups of car users and the activity of these policy measures will not be dependent on each other, from the car user's point of view. Here a car user is not influenced by multiple policy measures at once to avoid peak and these cases will therefore be treated as separately implemented policy measures. The criteria of when policy measures are interacting with each other are elaborated a bit further here below.

Active period of a policy measure

When there is no overlap in active period between policy measures, it cannot be the case that a group of car users is exposed to both policy measures at once, because this group is targeted at separate periods. Therefore, should this criterion be in place. The period during which a policy measure was active is dependent on the nature of that policy measure. For IPMs, the active period starts after completion of that policy measure until the end of the program, assuming that the infrastructural change is permanent. For BPMs, the active period is when the reached car users could participate in that policy measure.

Influencing a specific reached target audience

When there is no overlap in reached target audience, it cannot be the case that a group of car users is exposed to both policy measures at once, because two different groups are targeted. Therefore, should this criterion be in place. When the data is available, the reached target audience, which describes the group of car users that is influenced, can be very specific for BPMs. For instance, when commuters from a certain company or inhabitants of a certain residential area are targeted. However, this is not always the case. In some instances, only the type of car user or the area/corridor that is targeted is presented. This should then be used to describe the group of car users that is targeted, although it is not precise. The types of car users that are described in the action plans are commuters, inhabitants, visitors and students. When no further description is available this will be used to describe the group of car users targeted by the policy measure. It is possible for policy measures to transcend these categories, when multiple types are targeted or for IPMs, which all types can use.

It is also possible to describe a reached target audience by the area/corridor which is targeted. BPMs can be targeted to a specific area/corridor. However, it is possible to transcend this criterion, when car users are targeted in the entire region. IPMs do not have this problem because they are bound to a location, they are either located on a corridor or a node in the network.

Grouping BPMs that have interacted with another policy measure

To summarize, the following steps are taken to find out if a BPM interacted with another policy measure:

1. Determine the reached target audience and the active period for all policy measures.
2. Select a BPM.
3. Determine if the reached target audience matches with other policy measures.
4. Determine if the active period matches with other policy measures.
5. If both are true for another policy measure, that policy measure is then interacting with the selected BPM.

Table 4 shows a sample of the adjusted dataset. The full dataset is shown in

Table 32 which is located in the appendix, in section 9.1.

Table 4 – Sample of the adjusted BPM dataset from BBV

Code	Name measure	Name sub-measure	Measure category	Link with IPM	Bicycle and PT	Activity
HGL-BBV-001a	Projecten	KNMP	Bicycle demand	Yes	Yes	0.96
HGL-BBV-001b	Projecten	DB+	Bicycle demand	Yes	No	0.23
HGL-BBV-001d	Projecten	E-biketool	Bicycle demand	No	No	0.17
LWD-BBV-002b	Leeuwarden op de fiets	Rij2op5	Bicycle demand	No	No	0.10

2.4.3 BPM comparison

When it is known if a policy measure had interacted with others or not and if so what the configuration of that TMP was, the performance outputs of these policy measures can be analyzed. From Mayers et al., 2003 there are four main definitions to describe the combination of different TMPs. These combinations are: complementarity, additivity, synergy and perfect substitutability. These interaction possibilities are drafted up by looking at the welfare gain for policy instruments in transport packages. In this study, instead of welfare gain degree of participation, activity and effectiveness are the performance indicators of a BPM. The interaction possibilities that are mentioned are described as follows when two packaged policy instruments are compared to two separate policy instruments they are:

Complementarity, when the sum of the package is larger than both individual instruments:

$$(A + B) > A, and$$

$$(A + B) > B$$

Additivity, when the sum of the package is equal to the sum of both individual instruments. Note that this is also a form of complementary:

$$(A + B) = A + B$$

Synergy, when the sum of the package is greater than the sum of both individual instruments. Note that this is also a form of complementary:

$$(A + B) > A + B$$

Perfect substitutability, when the sum of the package is equal to both individual instruments:

$$(A + B) = A = B$$

Using these four definitions to describe the combinations of TMPs would be a good way to compare policy measures combinations belonging to a certain TMP configuration with policy measures that are independent. However, due to a lack of policy measures that are independent in BBV, no statistically significant answers can be derived when comparing policy measures from TMPs to independent policy measures. Using the data from BBV, the comparison can be made between groups of BPMs. All BPMs that interact with an IPM can be compared to all of those that do not have that link. When the sample sizes are large enough for both groups, the outputs of this comparison will give an indication of the difference in activity between certain groups. Having a large sample size also somewhat negates the effects of other impacts on the activity.

BPM comparison approach

Besides the configuration of a TMP, there are also other factors impacting the performance outputs of policy measures. These factors can be described as contextual characteristics. These are further elaborated in section 3.1.

The fact that these factors are of impact on the performance outputs of the BPMs makes it that the comparison between BPMs is not straightforward. This means that an approach should be found to make this comparison fairer.

A few possible approaches are listed here below.

1. Quantifying all contextual characteristics
2. Comparing BPMs to each other despite their contextual characteristics
3. Comparing BPMs with similar contextual characteristics
4. Use expert judgement to counter differences in contextual characteristics between BPMs

The choice is made to use a mix of the last three approaches. This is chosen because this will give a broader insight than straight-up comparing all aggregated data, while not being limited into only using the data from similar implemented policy measures. Because when that would be the approach very few usable data would remain. The combination of these approaches will be merged into a comparison over four observation levels. These observation levels are elaborated here.

Observation level 1: Analysis of all aggregate BBV-data

On the first observation level, the dataset, containing BPMs with their activities, is split into two groups. These two groups are formed using the characteristics that describes the hypothesis that is tested. The BPMs in the first group do not comply with the hypothesis and the BPMs in the second group comply with the hypothesis. The hypothesis will be tested by comparing these two groups in seeing if one has statistically significant higher activities than the other. Testing if a group has statistically significant higher activities is done by performing a two sample z-test. To be able to use samples in a z-test, the group needs to have a normal distribution. This is tested by performing a Kolmogorov-Smirnov test. The workings of a z-test and the reasoning why this test is selected is elaborated in the appendix in section 9.1.1. The same holds for the Kolmogorov-Smirnov test, which is elaborated in the appendix in section 9.1.2. Due to all available data being used in this comparison, this comparison will give a general overview on the hypothesis being true or not.

Observation level 2: Analysis of actual data compared to the expected values from measure category or region

On the second observation level the composition of the groups, from the first observation level, are analyzed. Here the impact of the measure category and region on the activity of the BPMs in the groups is investigated. The impact of measure category or region on the activity of the BPMs is mitigated by comparing the actual activity of the BPMs from these groups to the expected activity based on the overall averages of the measure categories or regions present in that group. This is done to not blindly come to conclusions based on the outcome of the comparison in the first observation level. Favorable measure categories or regions could have played a role in a group having higher activity values than the other. The comparison in the second observation level is started by first calculating the average activity values of all measure categories and regions. The expected average activity value is then calculated belonging to the two groups. This is based on the composition of these groups based on measure category or region. When these expected average activity values are calculated they can be compared to the actual data from that group. This is done by performing a one-sample t-test. This can show if the actual data from the groups is statistically significantly higher or lower than these expected average activity values. The workings of a one sample t-test are elaborated in the appendix in section 9.1.3.

Observation level 3: Analysis of BPMs from one measure category (a) or region (b)

On the third observation level, certain BPMs from the groups are selected for an analysis. Here the comparison will be made between BPMs from a single measure category or region. Due to these BPMs all belonging to a certain measure category or region the contextual characteristics of those BPMs should differ less, making the comparison between those fairer.

Observation level 4: Qualitative analysis of best performing BPMs from one measure category (a) or region (b)

On the last and fourth observation level, three individual BPMs will be examined. Here the best performing BPMs from the previous groups will be examined qualitatively to find out what could have caused them to achieve these high activities.

3 Literature study

This chapter is on the literature surrounding policy measures. First, the factors that can impact the performance of these policy measures are elaborated. Second, it is touched upon how these policy measures interact, while being part of a TMP. This is done to find out what advantages there are from implementing policy measures in a TMP over implementing them separately. The lessons learned will lead to a hypothesis on the impact of TMP configuration on the performance outputs of BPMs. This will be analyzed and tested in chapter 5 and chapter 6. In chapter 5, the degree of participation is analyzed and in chapter 6 the hypotheses will be tested based on the activity. Together these two factors make up the effectiveness of a policy measure.

3.1 Factors of impact on policy measures

When analyzing performance outputs of BPMs either in effectiveness, degree of participation or activity. It is important to know what caused these outputs. If it is unknown what caused these outputs, it is impossible to analyze them properly. Not knowing the impacts on these performance outputs also makes it difficult to recreate successes and prevent failures in future scenarios. The scope of this study is the analyzing the impact of the configuration of a TMP on the performance outputs of a BPM. However other factors could also play a role in impacting these outputs. This section is therefore to find out what other impacting factors there are.

Ben-Elia & Ettema (2011), whom performed an analysis on a 13 week field study in the Netherlands on the potential of rewards as a mean to change commuter behavior, state that in terms of the factors influencing commuter travel behavior, the results indicate that the reward is the primary factor affecting their choices and the likely trigger that stimulates commuters to consider changing their behavior. However, they also state that it is clear that this effect is mediated by other factors. These include socio-demographic characteristics, situational factors (home and work related), habitual behavior and experience, attitudes, travel information and even weather. Marsden (2007) states that key influences on behavior (for individuals and organizations) are attitudes, structural factors, knowledge and awareness, social and cultural norms, capability and self-efficacy, habit and costs. Eriksson et al., (2010) state that the goal to change travel behavior is influenced by individual factors, such as, background factors and psychological factors. In general, studies have demonstrated that background factors, for example, gender, age, income, and car access are important for travel behavior, although, psychological factors may be even more important. Bramberg et al., (2011) state that whereas car use predominantly depends on evaluations of positive and negative consequences for the car user, car-use reduction appears to depend more strongly on pro-social motives. They have also made a conceptual framework (Figure 8 in section 9.2, in the appendix) relating car users' decision making to the objective environment and socio-demographic factors, which frequently are evoked to account for disaggregate travel behavior. BPMs fall under the soft transport policy measures category and IPMs fall under the category of hard transport policy measures. Influences on the decision making and therefore the travel choice of the car users according to Figure 8 are socio-demographic factors, situational factors, trip chain attributes and the perception of the objective environment. Gärling et al., (2000) have made a conceptual framework. This is on car-use reduction intentions and their determinants. The conceptual framework is shown in Figure 9 in section 9.2, in the appendix. The determinants in this conceptual framework are: economic incentives, law regulation, needs, requirement and obligations, the environment, constraints, preferences and perceived costs and the transportation system. Gärling et al., (2002) have also made a conceptual framework. This is shown in Figure 10 in section 9.2, in the appendix. The impacts on travel demand management are: individual factors, situational factors, trip chain attributes, effects on others, public information and setting an adjustment goal and forming an implementation plan.

To summarize the impacting factors on travel behavior and therefore the impacting the performance outputs of policy measures are:

- Economic incentives
- Socio-demographic characteristics
- Situational factors (home and work related)
- Habitual behavior and experience
- Attitudes
- Travel information
- Weather
- Structural factors
- Knowledge and awareness
- Social and cultural norms
- Capability and self-efficacy
- Costs
- Psychological factors
- Pro-social motives
- Trip chain attributes
- The perception of the objective environment
- Law regulation
- Needs
- Requirement and obligations
- The environment
- Constraints
- Preferences and perceived costs
- Setting an adjustment goal and forming an implementation plan.

What stands out is that there are a lot of different factors of impact on travel behavior and therefore on the performance outputs of policy measures. Some of these factors are directly or indirectly altered by a policy measure and some are independent from policy measures of impact on the travel behavior.

It is clear that there are a lot of factors of impact on the performance outputs of a BPM besides the configuration of a TMP. If all other factors, listed here above, were the same for each analyzed BPM, a straight up comparison could be made between BPMs from a different TMP configurations to find that impact on the outputs of a BPM. This is however not the case, due to the BPMs being implemented across different regions the Netherlands on different groups of car users. This means that the differences in performance outputs of BPMs in the different scenarios cannot be attributed to solely the configuration of their respective TMP. Other factors were also playing a role in those differences. This is also noted throughout the analyses in chapter 5 and 6. The impact of different factors on the performance outputs is combatted a bit, by using data from 51 BPMs. The aggregate of more policy measures will decrease the impact of outside factors. In chapter 6, BPMs with similar characteristics are also compared to each other, to make the comparison fairer. This makes the analysis also more complete.

3.2 Known interaction effects in TMPs

3.2.1 Reasoning behind composing TMPs over independent policy measures

To get a grip on what the reasoning could be behind implementing TMPs over individual policy measures, scientific papers on the topic of TMPs are examined. Marshall & Banister (2000) conclude that the way forward would appear to lie in setting clear policy objectives and in assembling travel reduction measure into strategy packages, ensuring that when combined, measures are complementary towards policy objectives of travel reduction. The reasoning behind composing a TMP lies besides positively affecting the performance outputs of the policy measures, but it does indicate that there are other needs for implementing TMPs over individual measures. Although it is indicated that there are benefits in implementing TMPs, there is no statement added that this would be preferred over individual measures for the performance from a traffic standpoint. May et al., (2006) state that in a simple system, it seems unlikely that the application of two changes, which are mutually reinforcing should achieve more than the sum of parts. For example, an increase in frequency and a reduction in fare on a single bus route are both likely to increase patronage, but both will to some extent attract the same users, and the increase from both combined is likely to be less than that from the sum of their individual impacts. However, the transport-land use system in a city is not simple; interactions between modes and routes, lags in response and feedback between transport and land use could all potentially result in discontinuities in the impact of policy instruments, which could give rise to synergy. Essentially, when composing TMPs thought should be given into which policy measures share overlapping qualities in attracting the same users. The combination of such measures could be detrimental due to their combination being less effective than the sum of their parts. As May et al., (2006) stated, the reality could differ from what is theoretically expected. This is also where this study comes into play, where implemented policy measures are analyzed coming from different configurational TMPs or being individually implemented. Here hypotheses will be tested on what the effect is of the configuration of a TMP on the performance of a BPM. They also state that it may be that synergy is harder to achieve with a single objective, since the instruments that contribute to it will to some extent duplicate one another in their impacts. It may be that synergy becomes more apparent when objectives are in conflict, though much will then depend on the balance between these objectives. Although few of the studies that they reviewed were designed specifically to investigate synergy. It appears to them that complementarity effects are more of a realistic goal than synergy. In the BBV program, there was a single objective. This was to reduce the travel time of the most delayed vehicles with 10%, meaning that complementarity could be more realistic to be found than synergy, according to May et al., (2006). Erikson et al., (2010) Based their study on a review of several real interventions in European cities, where Marshall & Banister (2000) claimed that a combination of measures (e.g., restricting car use in the city center and improving facilities for cyclists and pedestrians) are likely to be more effective compared to single measures. Together the different studies (e.g., field experiments, studies of elasticities, and studies of hypothetical TDM measures) demonstrate that, to a limited extent, travel demand which is influenced by TDM measures and packages of different measures may increase behavioral effect. Overall though, the demonstrated pattern, adds to the studies showing that packages of TDM measures lead to larger behavioral responses compared to the individual TDM measures. Since the package makes both the cost for using the car higher as well as the cost for using alterative travel mode lower, more environmentally friendly travel modes become more favorable compared to if no measure or only one of the single measures would be implemented. This is in line with for example TPD Ajzen (1991), this change can result in a larger expected car use reduction as a result of a higher perceived behavioral control or more a positive attitude towards using alternative travel modes. It is however not possible to draw conclusions on the effects of push and pull measures in general based on this study. More studies are needed in order to examine different combinations of measures (e.g., various pricing strategies combined with improvements of alternative travel modes) in different types of studies (e.g., real life field experiments and scenario-based studies).

What can be learned from these studies is that there is already some knowledge on the implementation of TMPs and that there are multiple reasons behind implementing a TMP, besides improving the performance outputs of the policy measures in that TMP. However, it is also apparent that more research needs to be done to come to conclusive results in getting a grip on the interactions effects within these TMPs.

3.2.2 Positive impact of a TMP configuration on a policy measure

Heyns (2015) states that the key to managing traffic congestion in a sustainable way is to develop integrated strategies that cut across supply, demand and land-use management measures in forming a balanced package. Although land-use management measures are not present in BBV, it is interesting that the combination of supply and demand measures is being recommended as a balanced package. Gärling et al., (2002) state that it has become increasingly evident that travel results from choices people make that are both interdependent and dependent on desires or obligations to participate in activities. It may therefore be a mistake for any measure to solely focus on a target behavior, such as car use. It could therefore be of interest when composing TMPs to focus on more than one target behavior. Meaning that the increase of alternative modes could be coupled with the decrease of car use. Meyer et al., (1999) states that in almost all cases one major conclusion stands out. Some level of incentive or disincentive must be present to encourage automobile users to change their travel behavior. Even with incentives and disincentives, changing travel behavior at levels to make a difference would be problematic given the current reliance on the automobile for personal travel. Although it is beyond the scope of their paper to review all of the literature supporting this, some evidence that suggest the importance of some level of ‘‘coercion’’ to affect travel behavior follows. The combination of incentives and disincentives to construct a TMP would be an interesting combination to study. However, in BBV there is a lack of policy measures containing disincentives, which makes it not a viable option to analyze. Habibian & Kermanshah (2011) researched the interaction between transportation demand management policies in Teheran, by performing a stated preference questionnaire. These policies were increasing parking cost, cordon pricing, increasing fuel cost, transit time reduction and transit access improvement. They state that synergy emerges with the interaction between increasing parking cost and either cordon pricing or increasing parking cost. Cordon pricing and increased fuel cost had no synergy. Meaning that the effect of simultaneously implemented demand measures could lead to synergy. However, this synergy was between push measures (disincentives), which are not implemented enough in BBV to come to statistically significant conclusions. Eriksson et al., (2010) researched the impact of expected car reduction in response to a push measure (i.e. raised tax on fossil fuel), one pull measure (i.e. improved public transport) and the combination of the two. The combined measures led to a larger expected car use reduction compared to the measures individually. Again, showing synergy between two demand measures, being a combination of push and pull. Here similarly as for the previous study the results were based on data obtained from a questionnaire and no real-life application. May et al., (2006) states that a combination that involves increase in car operating cost by 75% potentially through fuel taxes or distance-based charges; reduction public transport journey times by 5% through bus priorities and similar measures; and halving public transport fares, shows significant synergy in its ability to attract trips to public transport, with an increase 35% higher than that from the sum of the constituent elements. There was also clear evidence of synergy for car trips and car-km. In this study push and pull measures were presented inside a TMP as well. Although, reducing transport journey times through bus priorities and similar measures can be classified as IPMs.

Meaning that the synergy could come from the combination of push and pull measures, the combination of BPMs and IPMs, or a combination of both. Lautso et al., (2004) state that the best results were achieved by using policy combinations, i.e. push and pull measures consisting of car pricing policies and simultaneous improvement of public transport through reduced fares and better speed and service. The combination of produced cumulative results and the negative land use effects of individual policies could be avoided. Here as well as the previous study the combination is made between push and pull, with the addition of IPMs. Bamberg et al., (2011) state that it should be noted that their conceptual framework stresses the interdependence of hard and soft transport policy measures. With the implementation of hard transport policy measures that change the relative attractiveness of travel options, the possibility increases that soft transport policy measures would be effective in motivating and empowering car users to switch to these options. Here it is apparent that hard and soft transport policy measures seem to be more effective when linking them together although they also state that additional research should illuminate how the simultaneous implementation of hard transport policy measures would increase the effectiveness of soft transport policy measures and vice versa.

3.3 Hypotheses obtained from the literature study

To summarize the packaging strategies obtained from the literature study, the following three combining strategies are constructed:

1. Push and pull
2. Supply, demand and land-use
3. Not solely target car use

These packaging strategies lead to hypotheses on TMP configurations that could be beneficial to the performance outputs of a policy measure.

1. Push and pull
When combining a push and pull measure in a TMP the performance of both policy measures will be higher than when implemented separately.

2. Infrastructural and behavioral

When combining a BPM with an IPM, both aimed to incentivize car users to switch to the same mode, the BPM will have a higher performance outputs than when implemented without that link.

3. Not solely car use

When the configuration of a TMP is constructed with measures focusing on multiple target behaviors the performance outputs of a policy measure could increase.

3.3.1 Link from the hypotheses from the literature study to the datasets

The hypotheses that are formulated in the previous section need to be able to be tested using the dataset from the travel behavior questionnaire and the BPM dataset from BBV. Otherwise no statements can be made on the validity of the hypotheses.

1. Push and pull

A hypothesis on the performance of push and pull measures cannot be tested using the BPM data from BBV. This is due to a lack of push measures. In total, there were 5 push measures taken. Making the comparison between push and pull measures and individually performed push and pull measures even more rare. This would not lead to statistically significant outcomes and results that could be generalized for other situations. This hypothesis is therefore not tested.

2. Infrastructural and behavioral

A hypothesis on the performance of IPMs and BPMs can be tested using the data from the travel behavior questionnaire and the BPM data from BBV. This results into the following hypothesis.

When a BPM aimed to incentivize car users to switch an alternate mode interacts with an IPM aimed to incentivize car users to switch to the same alternate mode, this BPM will have higher performance outputs compared to when this BPM would not be linked to such an IPM.

3. Not solely car use

A hypothesis on the performance of a combination on multiple target behaviors cannot be tested using the BPM data from BBV. This delves deeper into motives on why a traveler would not want to drive their car during peak hours. Although these motives are interesting to study, these are not targeted by BPMs in BBV.

4 Practical lessons learned from BBV

This chapter is on the practical side of implementing policy measures in TMPs. To be specific, policy measures implemented in the BBV program. This chapter will start with an analysis of the action plans, to get a better insight in what was already known about implementing TMPs before starting the BBV program. Then the evaluation of the policy measures will be discussed, to gain knowledge on what lessons have been learned from this program. Lastly, the conclusions are summarized and a hypothesis is formed on the TMP configurational impact on the performance outputs of BPMs.

4.1 'Beter Benutten Vervolg' program introduction

To increase the accessibility of the busiest urban areas in the Netherlands, the 'Beter Benutten Vervolg' program was initiated. This program was successive to 'Beter Benutten' (BB) and was executed on behalf of the former ministry of 'Infrastructuur & Milieu', now part of 'Infrastructuur & Waterstaat' (I&W). The objective of this program was to decrease the door-to-door travel time of the most delayed vehicles during peak hours with 10%. The focus of this follow-up program was to implement measures that give car users smart alternatives to reach their destination, next to travelling by car. To reach this goal, twelve participating regions took a variety of behavioral, infrastructural and ITS measures, with the idea to decrease the number of car users during peak hours or to increase the capacity of the road network. The focus however was on decreasing the intensity during peak hours. Having a decrease in intensity or an increase in capacity has the (initial) effect of increasing the throughput and therefore decreasing the travel time of delayed vehicles.

To come to this objective, all twelve regions together took 467 policy measures, divided over 179 TMPs. In this context, a TMP can consist of one or more behavioral, infrastructural or ITS policy measures, all combined into the same action plan, drafted by the respective regions who executed that TMP. Here below a summation of the policy measures is given, to show the variety of policy measures that were executed.

- BPM
    - Bicycle
    - Public transport
    - Multimodal transport
    - General
- IPM
    - Bicycle
    - Public transport
    - Multimodality
- ITS
- Incident management
- Logistics

The program officially lasted from 2015 until the end of 2017, although some policy measures went on past that date. This means that when starting this research, the program was in its evaluation phase and the outcomes from the measures were being presented. The twelve regions all were all responsible for the implementation of the measures, as well as the monitoring and evaluation. This monitoring and evaluation were usually outsourced to a consultancy, for instance MuConsult or Keyport. Ecorys then analyzed the monitoring and evaluation of the large and some of the medium size measure packages.

4.2 Practical knowledge before the start of BBV

To be able to find out what was known about the impact of implementing policy measures in TMPs. The action plans on these policy measures can be helpful. Here the regions that would implement the policy measures would give the number of expected peak avoidances for these measures and their reasoning behind that. When looking at the action plans it is clear that there was no real universal knowledge sighted on what the impact of the configuration of a TMP on the policy measures was. Illustrations on the estimations of impact in action plans of BBV are given here.

First, in an action plan from Metropoolregio Amsterdam concerning policy measures for the Zuidas, it is stated that due to the measures being aimed at partly the same target audience, a correction is performed on the ex-ante estimated peak avoidances of the entire TMP. Here the total of 1717 peak avoidances per working day, which is the sum of 800, 508 and 409 from the individual measures, is adjusted down to 1500 peak avoidances per working day. However, now further explanation is used on why this particular reduction was used. Making it seem just a guess why the total effects of the policy measures are reduced by 12.6%, instead of any other percentage.

Second, in an action plan from Midden-Nederland concerning policy measures for Utrecht Science Park and Rijnsweerd, it stated that for some of the BPMs partly due to strong cohesion between these measures, the effect of all of them are estimated together as one. However, they do not state what the individual contribution of these BPMs were and how the cohesion between them affected these individual contributions. When at the end combining the effects of the BPMs and the IPMs these are simply added up with one another. This would mean that they considered the effects of this combination as additive and therefore not impacting the number of each other’s peak avoidances.

Last, for an action plan in Maastricht, when estimating the total effect of the TMP, they took the sum of all individual measures. Here the impact of the combination seem to be additive, as well as the BPMs and IPMs from the previous example. However, they previously stated that there is a strong synergy between the individual measures. This is not reflected in the calculation. This means that the text contradicts the data or that the synergy effects were already implemented in the individual estimations. This was however not clear from the accompanying text.

These three cases illustrate that the regions had put some thought about the impact of the configuration of the TMP of the performance outputs of policy measures. Although the fact that these were rough estimations and not substantiated by previous studies or similar projects means that beforehand there was not much known about this impact.

4.3 Practical knowledge after BBV had ended

There was a lot of knowledge gathered after implementing all those policy measures. Most of that knowledge is important to in future projects but does not fall in the scope of this study. The few statement on the topic of interaction effects between policy measures are listed here below.

General peak avoidance projects were particularly effective during road works. This is due to being a good cause to change travel behavior. When combining this general peak avoidance measure with the stimulus of mobility services a lasting effect was noticed on the travel behavior of car users. One third of the participants is namely still avoiding peak two years later, even without rewards. In particular participants who switched to cycling or public transport keep avoiding peak at long term. This means that there could be benefit into combining multiple policy measures to change travel behavior. Car users are apparently more strongly influenced to change their travel behavior when they are influenced by multiple changes.

The BPM 'No Spits Today' from Midden-Nederland proved that the option for participants to choose how to avoid peak led to a high activity for these participants. The same holds for a BPM called 'Wild van de Spits' in Haaglanden. This holds that participants from BPMs could have a higher activity when they are able to choose how they want to avoid peak, according to the success from these BPMs.

4.4 Conclusions

It is clear that before and after BBV, there is still a lot to learn on the topic of impact on a BPM due to the configuration of the TMP. Although for certain configurations of TMPs the combined effectiveness is still uncertain, two main lessons can be learned from BBV. Namely, car users are more likely to change their travel behavior and keep that long term when they are exposed to multiple changes and participants from BPMs seem to have a higher activity when they get to choose how they avoid peak. This last lesson has been made into a hypothesis, to be tested for the entire BBV. This will be tested in chapter 6.

4.4.1 Hypothesis from the practical lessons from BBV

When a BPM aimed to incentivize car users to switch to an alternate mode interacts with another BPM aimed to incentivize car users to switch to a different alternate mode, this BPMs would have higher performance outputs than when they are not linked to such a BPM.

5 Travel behavior questionnaire analysis (degree of participation)

In this chapter the impact of a TMP configuration on the degree of participation of BPMs will be analyzed. The degree of participation is one of the performance outputs of a policy measure. It is the number of participants divided by the number of the reached target audience. Which essentially describes the attractivity of a policy measure. Analyzing this will lead to a better understanding of what it takes for a car user to participate in a single BPM, multiple BPMs or none. Together with the activity this will give an overview of the workings of a BPM. The activity will be analyzed in chapter 6 and the conclusions of both the degree of participation and activity will be in chapter 7.

The degree of participation from policy measures is analyzed by using questionnaire data on travel behavior. This data comes from the questionnaire 'Gedragsmeting Beter Benutten 2017'. This is a questionnaire that was performed for research purposes in context of 'Beter Benutten'. It was executed by I&O Research in commissioned by the ministry of I&M. Similar questionnaires were performed every year, beginning in 2012 when 'Beter Benutten' started. This was done to get a better view of the changes and similarities in travel behavior over the years. The respondents from this questionnaire are not necessarily linked to BBV, making the data that derives from the questionnaire independent from the BBV data used in chapter 6. The respondents are however Dutch car users from the same time period.

5.1 Description of the analyzed questions

The two questions which are analyzed are both part of a string of questions. To come to the analyzed question, first all respondents were asked if their car use had increased or decreased, relative to five years ago (question 75). When their answer would be that their car use had increased or decreased, they were asked the question why this had increased or decreased (question 76). In this question multiple answers were possible, two of them were improved possibilities to travel by bicycle or improved possibilities to travel by public transport. If respondents included one of these in their answer, they were presented with the question what had contributed to their bicycle travel possibilities being improved (question 77) or with the question what had contributed to their public transport possibilities being improved (question 78). At these questions, which are also the analyzed questions, the respondents were given the possibility to give multiple answers. The answer possibilities are shown in Table 5.

Table 5 - Answer possibilities (question 77 & 78, Gedragsmeting Beter Benutten 2017)

Nr.	Improved bicycle travel possibilities	Improved public transport travel possibilities
1	More parking spaces for bicycles at my employer	Shorter travel time
2	Better parking spaces for bicycle at my station or residence	Higher frequency
3	Bicycle infrastructure has improved on my route	Better connection
4	I own a better (e)-bike	More options
5	I can now make better use of a bicycle sharing system	Shorter walking distance
6	A different answer	Greater supply P+R
7	None of the above	A different answer
8	-	None of the above

5.2 Link between travel behavior questionnaire data and policy measures

The questions that are analyzed do not directly describe car reduction or peak avoidance due to policy measures. What they describe is car reduction due to improvements in bicycle or public transport travel. When wanting to use the outcomes of the questions to describe the degree of participation of policy measures (what it takes for car users to participate in a policy measure), there should be a link between the two. The link here is that BPMs and IPMs are implement to reduce car use at peak hours (at certain bottlenecks). A way of doing that is to incentivize car users to travel with a different mode, e.g. bicycle or public transport. These types of policy measures are also present in BBV. These policy measures are improving the alternative mode, which makes them more attractive to use. The answer possibilities of why car users had reduced their car use are also improvements to an alternative mode. Therefore, it is presumed that because these improvements can be the result of BPMs and IPMs, in this analysis they are seen as such.

Table 6 and Table 7 show the answer possibilities of the questions and their corresponding measure type counterpart (BPM or IPM). The answer possibilities 'A different answer' and 'None of the above' cannot be categorized as a policy measure and are therefore removed from the analysis. The tables also show the percentages which these answer possibilities were selected. Note that the sum of the answer possibilities is higher than 100, due to multiple answers being possible. The ability to give multiple answers also links to policy measures having the possibility to be implemented on their own or together in a TMP. Multiple improvements here are the equivalent of multiple policy measures being of influence on the same car user.

Table 6 - Answer distribution, reducing car use due to improved bicycle travel possibilities

Nr.	Bicycle travel improvement	Percentage	Measure type comparison
1	More parking spaces for bicycles at my employer	5.9	IPM
2	Better parking spaces for bicycles at my station or residence	15.1	IPM
3	Bicycle infrastructure has improved on my route	29.1	IPM
4	I own a better (e)-bike	77.9	BPM
5	I can now make better use of a bicycle sharing system	3.5	BPM

Table 7 - Answer distribution, reducing car use due to improved public transport travel possibilities

Nr.	Public transport travel improvement	Percentage	Measure type comparison
1	Shorter travel time	26.6	BPM
2	Higher frequency	52.6	BPM
3	Improved connection	43.6	IPM
4	More options	32.8	IPM
5	Shorter walking distance	33.5	IPM
6	More P+R options	11.6	IPM

Figure 4 visualizes what the data from this question describes. The dataset consists of the car users that have reduced their car use, due to having their bicycle or transport travel improved. When making the link to BBV, these car users would be participants in one or more policy measure(s). They are successfully persuaded to take part in that policy measure, meaning that they are reducing their car use. However, due to this not being quantified, the activity of these participants cannot be determined. The degree of participation can also not be quantified using this data. This is because only the car users that had reduced their car use were asked these questions, meaning that the car users that had their bicycle or public transport travel improved but did not reduce their car use are not present in this dataset. Because only car users that have reduced their car use are present in this dataset, the degree of participation cannot be quantified.

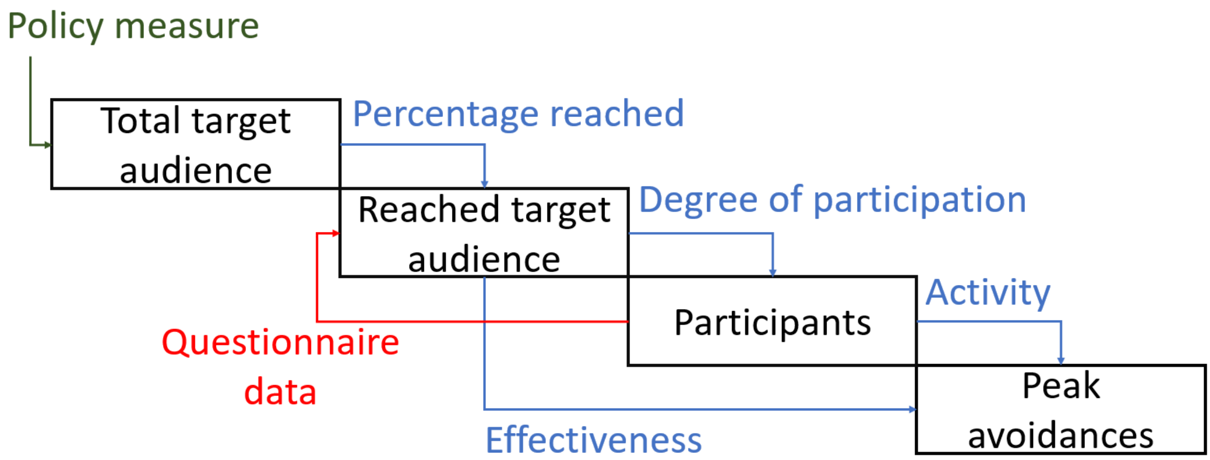

Figure 4 – Place of the questionnaire data in the waterfall diagram of (performance) outputs of a policy measure

Not being able to quantify the degree of participation does not give a complete view of the implications on car use, when car users are presented with multiple policy measures incentivizing bicycle or public transport travel. The bias in the data that is described here is called the survivor bias. Here only the successful examples are presented in the data, which in this case are the car users that have reduced their car use. It does however give an insight in what policy measures can work well together in persuading car users to reduce their car use.

Another note is that if the most respondents selected a certain improvement as their reason to reduce car use, it does not necessarily mean that this improvement would have the highest degree of participation.

5.3 Analysis of the travel behavior questionnaire data

When removing the respondents that chose ‘A different answer’ and ‘None of the above’, 750 respondents remain for having their bicycle travel being the reason to reduce their car use and 561 respondents due to having their public transport travel being that reason. The distribution of their answers is shown in Table 6 and Table 7.

What can be seen from Table 6 is that owning a better (e)-bike is by far the most selected reason to reduce car use. It is selected more times than all other bicycle travel improvements combined. Table 7, shows that having their public transport travel with a higher frequency is the most selected reason to reduce car use. Here the other improvements are however a lot closer in number of times being selected compared to the answers from the bicycle travel improvements.

5.3.1 Confounding the interaction impact of a IPM on the degree of participation of BPMs (hypothesis 1)

The answering possibilities of the questions allow to analyze the impact of the combination of behavioral and infrastructural improvements on car reduction. This is in line with section 3.3, where a hypothesis is formed that the performance outputs of a BPM would be higher if these would interact with IPM incentivizing the switch to same alternative mode.

Using this dataset we can see what the impact is of the interaction of infrastructural improvements to behavioral improvements. How the percentage of being selected changes when these are linked and to see at which rates these differences occur.

To start with the bicycle travel improvement question, the option of owning a better (e)-bike (option 4) is looked into. The percentage which this option was chosen individually was 57.3. Table 8 shows the maximum total percentages which owning a better (e)-bike is chosen in combination with one or more infrastructural improvements. Here both the absolute and relative percentage changes are shown. These are compared to the previous combination, with one less infrastructural improvement. Figure 5 shows the highest extra percentages of the combination of owning a better (e)-bike with at each step an infrastructural improvement added. The blue percentages show the absolute added percentage on the left and the relative added percentage on the right. The relative added percentage is compared to the previous combination.

Table 8 – Maximum extra percentage of participants when adding one infrastructural improvement at a time to owning a better (e)-bike

Combination	Combination	Percentage	Extra percentage	Extra percentage (relative)
Individual	4	57.3	-	-
One IPM	3 & 4	69.1	11.7	20.5
Two IPMs	2, 3 & 4	73.7	4.6	6.8
Three IPMs	1, 2, 3 & 4	76.5	2.8	3.8

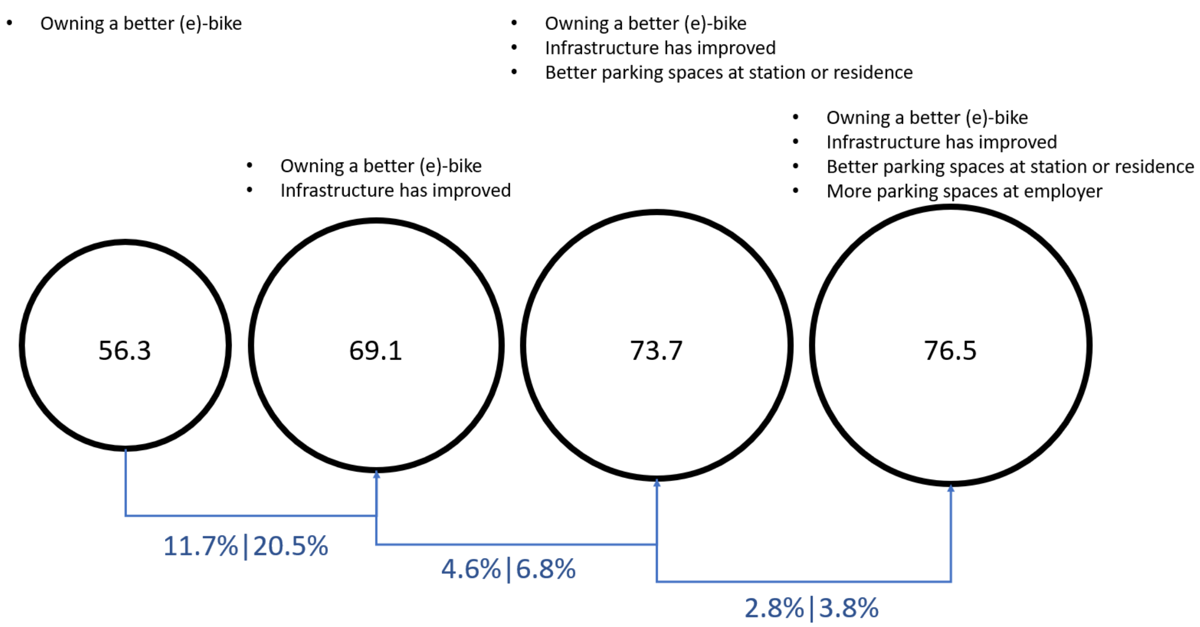

Figure 5 – Extra percentage of participants when adding one infrastructural improvement at a time to owning a better (e)-bike

Table 8 and Figure 5 indicate that there is a group of car users (influenced by a behavioral improvement of bicycle travel) that also needs infrastructural improvements in bicycle travel to reduce their car use. These car users are represented by the extra percentages each time an infrastructural improvement was added. What can be seen here is that the new group of car users that reduces their car use to an extra infrastructural improvement decreases as the number of added infrastructural improvements increases, both absolute and relative to the previous group. This means that when wanting to maximize the additional effect of implementing a infrastructural improvement on top of a behavioral improvement, it may not be wise to simple stack a lot of these improvements together. This due to having depleting extra effects. Adding infrastructural improvements do however achieve a higher total number of participants in the behavioral improvement, just slightly less each time. This could be useful when a certain threshold of participants needs to be obtained to combat specific traffic issues.

For more of a complete image Figure 6, shows Venn-diagrams of the absolute extra percentages and the total percentages due to combining the three infrastructural improvements to owning a better (e)-bike. The percentage within a circle represents the percentage of car users that reduced their car use due to that specific combination. The percentage within a circle without overlap represents the car users from a single combination from that infrastructural improvement on top of owning a better (e)-bike. The percentages within a circle with overlap represents car users reducing their car use due to a combination of infrastructural improvements on top of owning a better (e)-bike. The left Venn-diagram shows the additional percentage of car users and the right shows the total percentage of car users choosing the combinations.

1. More parking spaces at employer
2. Better parking spaces at station or residence
3. Infrastructure has improved

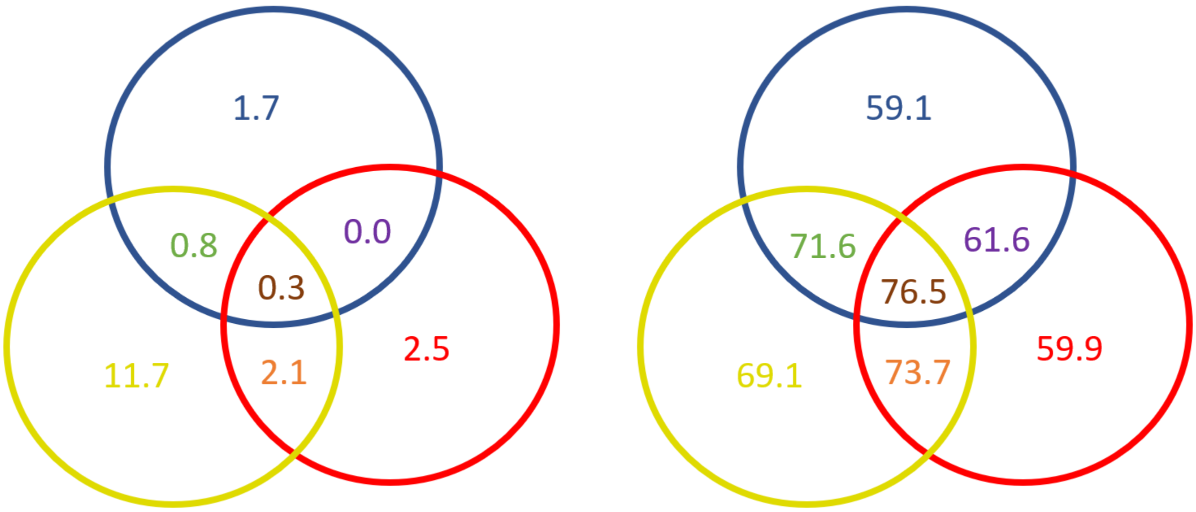

Figure 6 – Venn-diagram of additional percentages of car users reducing their car use, due to the combination of infrastructural improvements with owning a better (e)-bike

What can be seen here is that the magnitude of the extra percentages from the combinations of infrastructural improvements with owning a better (e)-bike differ quite a bit. This is depending on the which infrastructural improvement is part of that combination. This could indicate that when wanting to come to the maximum additional effects, chosing the 'right' combination is important. In this example, having an improved bicycle route seems to have the highest extra percentages when combined with owing a better (e)-bike. This does not necessarily mean that the other two improvements are not to be used in a combination with owning a better (e)-bike. It just means that when looking from the behavioral improvements point of view, improving the bicycle route had the highest number of extra respondents that was influenced to reduce their car use due to this combination.

Owning a better (e)-bike is also the only improvement that was selected less in combination than separately. This can be seen in Table 9, where the percentages of being chosen separately and in combination are shown.

Table 9 – Bicycle travel improvements selected separately or in combination with other improvements

Nr.	Bicycle travel improvements	Separately	Combination
1	More parking spaces for bicycles at my employer	29.5	70.5
2	Better parking spaces for bicycles at my station or residence	30.1	69.9
3	Bicycle infrastructure has improved on my route	30.3	69.7
4	I own a better (e)-bike	73.6	26.4
5	I can now make better use of a bicycle sharing system	19.2	81.8

Table 9 shows that only owning a better (e)-bike was chosen more as an individual improvement than as being part of a combination of improvements. This is in contrast with making better use of a bicycle sharing system, which is chosen much more in a combination of improvements compared to being chosen individually, same as for the three infrastructural improvements. This could indicate that owning a better (e)-bike when being the result of a BPM could be implemented separately and would not necessarily need a link to other policy measures to be successful in obtaining participants. Whereas the other policy measures seem to need a link with at least another policy measure to obtain participants. This could indicate that these should be implemented in a TMP, rather than separately. This result could also be due to the fact that owning a better (e)-bike is more of a commonly occurring improvement compared to the other five, making that the reason why this improvement is chosen more.

Analysis on the other behavioral improvements

When performing the same analysis for the other three behavioral improvements (being able to make better use of a bicycle sharing system, shorter travel time and higher travel frequency possibilities) as has been done for owning a better (e)-bike, similar results are found. The outcomes lead to similar patterns when linking those behavioral improvements to infrastructural improvements. Due to this similar nature, the analysis of these behavioral improvements is not shown in this section. For a complete overview, the figures and tables with the results for the other three behavioral improvement combinations are added in the appendix, in section 0.

5.3.2 Confounding the interaction impact of a BPM incentivizing the switch to a different mode, on the degree of participation of BPMs (hypothesis 2)

The answering possibilities of the questions allow to analyze the effects of the combination of a behavioral improvement of bicycle travel and public transport travel, on car reduction. This is in line with section 4.4.1, where a hypothesis is formed that the performance of BPMs would be higher if these would interact with another BPM incentivizing the switch to a different mode.

Besides looking at the impact of infrastructural improvements on behavioral improvements. The combination of respondents that selected both bicycle and public transport travel improvements, as their reason to reduce car use can be analyzed. As been said before, 903 respondents selected bicycle travel improvements and 561 selected public transport improvements. This results in a total of 1464 respondents. From that total, 160 respondents selected both. This means that 10.9% of the respondents were influenced by both improvement types and 89.1% by only one of those. This means that only a small percentage of the total group of car users that is influenced by these improvements needs both forms of travel to be improved to reduce their car use. This small overlap could indicate that when implementing bicycle and public transport policy measures, these two could steal participants from each other. This due to only a small percentage of car users needing both types to reduce their car use. This makes them only chose one of the options.

5.3.3 Why would a car user not participate in a BPM (e-bike program)?

The data which is analyzed in this section is on reasoning why car users would not want to participate in a behavioral policy measure, in this case an e-bike program. To make a policy measure successful, the car users should want to reduce their car use due to the improvements from the policy measure. However, the quality of improvement of another mode and TMP configurational impacts are not the only reason of participating in a policy measure or not. To find out more about reasoning why not to participate in a policy measure another question from the questionnaire is analyzed.

A question was asked on the reasoning why respondents did not want to participate in an e-bike program. The question was asked to all respondents that were invited to partake in an e-bike program but did not participate. The question was asked to 1251 of the respondents and multiple answers were possible. Table 10 shows the answer distribution of that question.

Table 10 - Answer distribution, reasons not to participate in an e-bike program

Nr.	Reasoning	Percentage chosen
1	Reward too low	5.7
2	No good alternatives	19.0
3	Too much hassle	18.4
4	Privacy reasons	5.1
5	I did not comply	22.1
6	Satisfied at my current way of travelling	26.8
7	Cycling is not for me	7.4
8	A different answer	22.6

'I did not comply' and 'a different answer' are excluded from the analysis. This because when a respondent did not comply with the rules of the program, that respondent was not part of the target audience of that program and therefore not of interest of a policy measure. Respondents that selected 'A different answer' are cut, due to the unclarity of the reasoning not to partake in an e-bike program. It is good to note that because it is quite a large share of the respondents that are cut due to having a different answer, that there are more important reasons for people not to partake in an e-bike program, besides the ones listed here.

Deleting the respondents that selected those answers leave 704 respondents. The distribution of their answers is shown in Table 11, together with a categorization of the reason.

Table 11 - Answer distribution, reasons not to participate in an e-bike program. With categorization.

Nr.	Reasoning	Percentage chosen	Category
1	Reward too low	8.5	BPM, quality
2	No good alternatives	28.3	IPM, quality
3	Too much hassle	29.1	Measure execution
4	Privacy reasons	8.5	Measure execution
5	Satisfied at my current way of travelling	44.9	Travel behavior
6	Cycling is not for me	11.9	Travel behavior

Table 11 shows that not just the quality of the policy measure is the reason behind car users not to participate in an e-bike program. A similar percentage of the respondents had their reasoning be that is was too much hassle or due to privacy reasons. This can be combated by a better execution of policy measures. By making the policy measures easy to join and stating clear conditions of maintaining the privacy of the participants, these respondents could be persuaded to join. The largest share of the reasoning why not to participate in an e-bike program is due to the travel behavior of the respondents. Due to them either being satisfied at their current way of travelling or not wanting to cycle despite cycling being made more attractive. This group would be difficult to persuade in participating in such a policy measure. They would perhaps be more inclined to participate if their current way of travelling would be less attractive. Unfortunately, in BBV there are very few policy measures that push car users away from their car, making this not a likely path to attract more participants for a policy measure.

5.4 Conclusions

Improving the possibilities to travel by bicycle or public transport can be a reason to reduce car use. Sometimes both are even needed for a car user to reduce their car use. When answering what contributed in these improvements, single and multiple improvements were given as answers. Most car users that chose bicycle travel improvements as their reason to reduce car use chose a single improvement, meaning that for incentivizing bicycle travel a single BPM can be effective enough for participants to partake in that measure. For public transport travel improvements this was the other way around. Here the majority chose a combination of improvements as their reason to reduce their car use. This could mean that when wanting to draw up policy measures to reduce car use or increase peak avoidance, for incentivizing bicycle travel a single improvement can be enough, but for public transport travel multiple improvements are needed in a TMP to attract participants.

When linking infrastructural improvements to behavioral improvements an additional number of car users is persuaded to reduce their car use. These car users could only be persuaded to reduce their car use due to both of these improvements being implemented. This additional effect decreases each time a new infrastructural improvement is added. This means that it could be interesting when wanting to increase participants of a BPM to link this with IPMs. This link to an IPM could therefor increase the degree of participation of BPM. However, this loses effectivity each time another IPM is added. It is also of importance that between combinations there is a quite a difference in additional participants. A fitting match should therefore be found to maximize those additional participants.

When linking behavioral improvements to improve bicycle and public transport travel, there is only a small percentage of car users that need both improvements to reduce their car use. Only 10.9% need both of these improvements to reduce their car use. This low percentage of overlap between participants needing both modes to improve to reduce their car use would result into a lower degree of participation for linked BPMs that incentivize bicycle and public transport travel.

The additional effect that the combination of a BPM with IPMs achieve in this questionnaire are car users becoming participants in BPMs. This phenomenon can unfortunately not be tested using the BPM data from BBV, due to a shortage of data on the number of the reached target audience for the BPMs. Vice versa can the BPM data obtained from BBV concerning the activity of participants not be validated using the data from this questionnaire. The conclusions from both chapters therefore independently lead to overall conclusions in chapter 7.

Besides the quality of a policy measure and their combination with other policy measures, the way which a policy measure is executed is equally as important for car users not to participate in that measure. Overcoming this hurdle can therefore also lead to an increase in participants, equal to creating the best fitting type of quality policy measures.

6 Activity (BBV data analysis)

In this chapter, the hypotheses that were formed in chapter 3 and 4 are tested. This is done by analyzing the data from BPMs implemented in the BBV program. This data only allows to analyze the activity of a BPM. The activity together with the analyzed degree of participation, analyzed in chapter 5 will give a view of the workings of BPMs, while interacting with other policy measures. The activity throughout this study is quantified in peak avoidances per participant per day (pa/pp).

6.1 Hypotheses testing

To recap, the hypotheses that are composed in chapters 3 and 4, are formulated as follows:

1. **When a behavioral policy measure aimed to incentivize car users to switch modes is linked with an infrastructural policy measure, aimed to incentivize the same car users to switch to the same mode, this policy measure will have a higher activity than when they are not linked to such an infrastructural policy measure.**

2. **When a behavioral policy measure aimed to incentivize car users to switch modes is linked with another behavioral policy measure aimed to incentivize the same car users to switch to a different mode, the activity of participants would be lower than when this is not the case.**

The outcomes of the analyses are put together in Table 12. When filled in, this will give an overview of the hypothesis being true or not over the different tested observation levels, within certain confidence intervals. The way that the tests are executed is elaborated in section 2.4.3, with some added elaboration in the appendix in sections 9.1.1, 9.1.2 and 9.1.3.

Table 12 - Main findings of testing the hypotheses over all observation levels

<table>
<tr><th></th><th colspan="2">Hypothesis 1: higher activity when interacting with an IPM?</th><th colspan="2">Hypothesis 2: higher activity when given multiple options to avoid peak?</th></tr>
<tr><td>Observation level 1</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>Observation level 2a (category)</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Observation level 3a (category)</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>Observation level 2b (region)</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Observation level 3b (region)</td><td colspan="2"></td><td colspan="2"></td></tr>
</table>

6.1.1 Confounding the interaction impact of a IPM on the activity of BPM (hypothesis 1)

Observation level 1: Analysis of all aggregate BBV-data

The dataset is split into two, where the first group contains BPMs that do not have a link with IPMs and the second group contains BPMs with a link to IPMs that incentivize to switch to the same mode. The total dataset consists of 51 BPMs, 35 of those belong to the first group and 16 belong to the second group. When executing the one-sided z-test on both groups, the following outcome arises, seen in Table 13.

Table 13 – Hypothesis 1, observation level 1. Outcome z-test all aggregate data

	Without IPMs	With IPMs
Average activity	0.331	0.420
Sample variance	0.0928	0.0817
Observations	35	16
z	-1.087	
P(Z<=z) one-sided	0.1385	

The z-score, from the performed z-test has a value of -1.09. This means that the absolute z-value lies between 0.842 and 1.282, which are the critical values corresponding to an alpha of 0.20 and 0.10, see Table 33 in the appendix section 9.1.1. This means that the second group contains statistically significant higher activity values than the first, within a confidence interval of 80 percent.

Conclusion

The outcome of the z-test results in the hypothesis being possible for this dataset, within a confidence interval of 80 percent.

Observation level 2a: Analysis of actual data compared to the expected values from measure categories

To delve into the impact of the measure categories on the activities of BPMs in the groups from the previous observation level, the configuration of the groups, based on the measure category is dissected here. This is done by comparing the actual activities of the groups to the expected average value of the groups. How the expected average value of the groups is calculated is shown in the section 9.4.1 in the appendix. This comparison is done by performing a t-test. The outcomes of these t-tests are given in Table 14.

Table 14 - Hypothesis 1, observation level 2a. Outcomes t-test based on measure category

	Without IPMs	With IPMs
Average activity	0.331	0.427
Sample variance	0.0928	0.0818
Observations	35	16
Expected average	0.348	0.391
T	-0.322	0.504
P(T<=t) one-sided	0.375	0.311

Table 14 shows a t-statistic of -0.32 for the group without a link to IPMs and a t-statistic of 0.50 for the sub-set with a link to IPMs. The absolute values of both of the t-statistics are lower than 0.842. This means that although the group without a link to IPMs has an actual average activity which is lower than the expected average and the group with a link to IPMs has an actual average activity which is higher than the expected average, they are not statistically significant lower of higher than these expected average values within a confidence interval of 80 percent.

Conclusions

The t-statistics for both groups are lower than 0.842, meaning that the groups are not performing statistically significantly better or worse than the expected average values within a confidence interval of 80 percent. This would indicate that the statistically significant outcome from the first observation level was more likely the result of the configuration of the groups, based on measure category than due to being linked to an IPM or not.

Observation level 3a: Analysis of bicycle demand measures

On this observation level a certain number of BPMs from both previously mentioned groups are compared to each other. Here only BPMs with the same measure category are compared to each other. For this comparison the measure category 'bicycle demand' is chosen, due to this measure category having a significant number of BPMs available in both groups. The sub-group without a link to IPMs contains 10 BPMs and the sub-group with a link to IPMs contains 12 IPMs. A z-test is performed on both of these groups and the following outcome arises, shown in Table 15.

Table 15 – Hypothesis 1, observation level 3a. Outcome z-test based on bicycle demand

Bicycle demand	Without IPMs	With IPMs
Average activity	0.297	0.375
Sample variance	0.0701	0.0883
Observations	10	12
z	-0.650	
P(Z<=z) one-sided	0.258	

What can be seen from the outcome of this z-test is that the z-score is -0.65. The absolute value of that z-score is lower than 0.842, meaning that the group with a link to IPMs is not statistically significant higher than the group without a link to IPMs, within a confidence interval of 80 percent.

Conclusions

The absolute z-score is lower than 0.842, meaning that for this observation level although there are differences in activity between the sub-groups, this difference is not statistically significant. This means that for measures categorized in the 'bicycle demand' category there is no reason to suspect that these measures have a higher activity when they are paired with measures that improve bicycle infrastructure.

Observation level 4a: Qualitative analysis of best performing bicycle demand measures

The next and last observation level is used to analyze three of the best performing measures from a single measure category. Complying with the previous observation level the measures category 'bicycle demand' is chosen. The best performing measures are based on the level of activity from the participants within that measure. The three scoring the highest are shown in Table 16.

Table 16 – Hypothesis 1, observation level 4a. Best performing bicycle demand measures

Measure	Link to IPM	Region	Participants	Peak avoidances	Activity
KNMP	Yes	HGL	68	65	0.956
E-bike	Yes	MNL	57	53	0.930
Shared bicycles	No	MRA	21	20	0.952

What can be seen from the best performing BPMs concerning cycling, is that they are all policy measures with a relatively low number of participants. An explanation why these 'smaller scale' policy measures could have a higher activity than 'larger scale' policy measures is that these are more manageable. They target a specific group of travelers which could be inclined to avoid peak. This in contrast to 'larger scale' policy measures, which could be less efficient due to not only targeting the 'right' car users with that measure. Here chance on targeting car users not interested in cycling is higher due to the larger scale of that policy measure. This would result into the participants not being that active in avoiding peak in larger scale policy measures. Although an interesting theory, there was not correlation found between the size of the BPM and the activity within this dataset.

Conclusions

The BPMs concerning bicycle transport that have the highest activity seem to be measures that also have a low number of participants.

Observation level 2b: Analysis of actual data compared to the expected values from regions

A second categorization of the BPMs within the groups is to categorize them by the region in which they are implemented. These regions are Haaglanden, Leeuwarden, Maastricht, Midden-Nederland, Metropoolregio Amsterdam, Noord-Brabant and Zwolle-Kampen. This is done by comparing the actual activities of the groups to the expected average value of the groups. How the expected average value of the groups is calculated is shown in section 9.4.1 in the appendix. This comparison is done by performing a t-test. The outcomes of these t-tests are given in Table 17.

Table 17 – Hypothesis 1 observation level 2b. Outcomes t-test based on regions

Regions	Without IPMs	With IPMs
Average activity	0.331	0.427
Sample variance	0.0 928	0.0817
Observations	35	12
Expected activity	0.371	0.339
t	-0.778	1.226
P(T<=t) one-sided	0.221	0.120

What can be seen from Table 17 is that the t-score for the sub-group without a link to IPMs is -0.78. The absolute value of that t-score is lower than 0.842, meaning that within a confidence interval of 80 percent, this sub-group is not statistically significantly lower than the expected average value. The t-score for the sub-group with a link to IPMs is 1.23, which is absolute value is between 0.842 and 1.282. This means that this sub-group is statistically significantly higher than the expected average value within a confidence interval of 20 percent.

Conclusions

The result of the t-test indicates that there is a possible increase in activity of participant from a BPM, when they are linked to an IPM, while taking the expected regional average activity into account. This can however not be said about the decrease in activity when BPMs are not linked to IPMs, due to not having a statistically significant decrease to the expected average.

Observation level 3b: Analysis of BPMs from MNL

On this observation level a certain number of BPMs from both previously mentioned groups are compared to each other. Here only BPMs from the same region are compared to each other. For this comparison the region Midden-Nederland (MNL) is chosen, due to this measure category having a significant number of BPMs available in both groups. The sub-group without a link to IPMs contains 8 BPMs and the sub-group with a link to IPMs contains 9 IPMs. A z-test is performed on both of these groups and the following outcome arises, shown in Table 18.

Table 18 – Hypothesis 1, observation level 3b. Outcome z-test based on MNL

MNL	Without IPMs	With IPMs
Average activity	0.174	0.371
Sample variance	0.0133	0.0803
Observations	8	9
z	-1.912	
P(Z<=z) one-sided	0.0280	

What can be seen from Table 18 is that the absolute value of the z-score is higher than 1.645, meaning that the activity of BPMs linked to IPMs are statistically significantly higher than those who are not. This is within a confidence level of 95 percent.

Conclusions

BPMs in the region of Midden-Nederland probably have a higher activity when linked to IPMs.

Observation level 4b: Qualitative analysis of best performing bicycle demand measures

Zooming in to the fourth observation level, the three-best performing BPMs from the combined sub-groups that are executed in MNL are analyzed. These are shown in Table 19.

Table 19 – Hypothesis 1, observation level 4b. Best performing MNL measures

BPM	Link to IPM	Category	Participants	Peak avoidances	Activity
E-bike	Yes	Bicycle	57	53	0.930
Emergency lane bus	Yes	PT	637	419	0.658
Bicycle map new inhabitants	Yes	Bicycle	336	170	0.506

The best performing measures are all linked to infrastructural policy measures, which is to be expected due to these being significantly higher than the other group (z-test in the previous level). What also can be seen in that two of the three measures are aimed at bicycle transport while one is aimed at public transport (which is the only one in that region). Bicycle and PT measures outperform general and employer measures in this region.

Conclusions

Bicycle and PT measures outperform general and employer measures in the Midden-Nederland region.

6.1.2 Confounding the interaction impact of a BPM incentivizing the switch to a different mode, on the activity of BPMs (hypothesis 2)

Observation level 1: Analysis of all aggregate BBV-data

To test the second hypothesis only the BPMs from the measure categories 'bicycle demand' and 'PT demand' are used. This will give a fairer comparison when analyzing the impact of another BPM that incentivizes another mode to BPMs that themselves incentivize a mode. Because these categories of BPMs are the only ones containing BPMs that might comply with that hypothesis. This means that this total dataset consists of 35 BPMs. This dataset is split into two, where the first group contains BPMs that do not have a link with a BPM that incentivizes another mode and the second group contains BPMs with a link to another BPM that incentivizes another mode. This holds that the first group contains 20 BPMs and the second group 15 BPMs. When executing the one-sided z-test on both groups, the following outcome arises, seen in Table 20.

Table 20 – Hypothesis 2, observation level 1. Outcomes z-test all aggregate data

	Single option	Multiple options
Average activity	0.266	0.570
Sample variance	0.049	0.149
Observations	20	15
z	-2.735	
P(Z<=z) one-sided	0.003	

The z-score for these groups has a value of -2.735. The absolute value is above 1.645, corresponding to an alpha of 0.05, see Table 20. This means that the second group contains values that are higher than the first, within a confidence interval of 95 percent.

Conclusions

The outcome of the z-test results in the hypothesis being probable, for this observation level.

Observation level 2a: Analysis of actual data compared to the expected values from measure categories

To delve into the impact of the measure categories on the activities of BPMs in the groups from the previous observation level, the composition of the groups, based on the measure category is dissected here. This is done by comparing the actual activities of the groups to the expected average value of the groups. How the expected average value of the groups is calculated is shown in section 9.4.2 in the appendix. This comparison is done by performing a t-test. The outcomes of these t-tests are given in Table 21.

Table 21 – Hypothesis 2, observation level 2a. Outcomes t-test based on measure category

	Single option	Multiple options
Average activity	0.266	0.570
Sample variance	0.0490	0.1490
Observations	20	15
Expected average	0.361	0.443
T	-1.918	1.279
P(T<=t) one-sided	0.070	0.111

Table 21 shows a t-statistic of -1.92 for the group with a single BPM incentivizing car users to switch modes and t-statistic of 1.28 for the subset for BPMs incentivizing car users to switch modes whom are also incentivized by another BPM to switch to a different mode. The absolute value of -1.92 is higher than 1.645, making the actual data being higher than the expected data within a confidence interval of 95 percent. The absolute value of 1.28 is between 0.842 and 1.282, making the actual data higher than the average data within a confidence interval of 80 percent.

Conclusions

It is probable that the group for single option BPMs has higher values than the expected average values, based on the measure category of the composition. It is also possible that the actual values for multiple option BPMs are higher than the expected average values, also based on the measure category of the composition.

Due to the differences between groups and the expected average values (based on measure category) are still statistically significant on this level, the notion of performing better or worse when packaged with another BPM that is incentivizing car users to switch to a different mode still stands.

Observation level 3a: Analysis of bicycle demand measures

On this observation level a certain number of BPMs from both previously mentioned groups are compared to each other. Here only BPMs with the same measure category are compared to each other. For this comparison the measure category 'bicycle demand' is chosen, due to this measure category having a significant number of BPMs available in both groups. The sub-group without a link to other BPMs with the incentive to switch modes contains 16 BPMs and the sub-group with that link contains 6 BPMs. A z-test is performed on both of these groups and the following outcome arises, shown in Table 22.

Table 22 – Hypothesis 2, observation level 3a. Outcomes z-test based on bicycle demand

Bicycle demand	Single option	Multiple options
Average activity	0.266	0.534
Sample variance	0.0407	0.1234
Observations	16	6
z	-1.750	
P(Z<=z) one-sided	0.040	

What can be seen in Table 22 is that the absolute value of the z-score is higher than 1.645. This indicates that within a confidence interval of 95 percent, the sub-set were a BPM is aimed to incentivize car users to switch to cycling is impacted by BPMs aimed to incentivize the same car users to switch to public transport are outperforming BPMs in that same category (cycling) who are not impacted by other category BPMs.

Conclusions

This means that it is probable that participants in BPMs incentivizing car users to switch to cycling have a higher activity when these are also influenced by BPMs incentivizing them to switch to public transport, in contrast to them only having that the single option to switch to cycling.

Observation level 2b: Analysis of actual data compared to the expected values from regions

A second categorization of the BPMs within the groups is to categorize them by the region in which they are implemented. These regions are Haaglanden, Leeuwarden, Maastricht, Midden-Nederland, Metropoolregio Amsterdam, Noord-Brabant and Zwolle-Kampen. This is done by comparing the actual activities of the groups to the expected average value of the groups. How the expected average value of the groups is calculated is shown in section 9.4.2 in the appendix. This comparison is done by performing a t-test. The outcomes of these t-tests are given in Table 23.

Table 23 – Hypothesis 2, observation level 2b. Outcome t-test based on regions

Regions	Single option	Multiple options
Average activity	0.266	0.570
Sample variance	0.0490	0.1490
Observations	20	15
t	-0.637	0.423
P(T<=t) one-sided	0.266	0.340

What can be seen from Table 23 is that the t-scores are -0.637 and 0.423 for both sub-groups. The absolute values of these are both lower than 0.842, meaning that they are not statistically significantly lower or higher than the expected average.

Conclusions

Having no statistically significant decrease in activity for BPMs with single options to avoid peak and no statistically significant increase in activity for BPMs linked to another option to avoid peak, compared to the expected average of a region, suggests that the differences in the sub-sets from observation level 1 could have been due to other factors than the TMP configuration. There are namely regional factors playing a role in getting differences between these sub-sets, based on this dataset.

6.2 Observed activity by measure category

When analyzing the BBV data, it became visible that BPMs belonging to different measure categories also had quite a difference in average activity. In this section, these differences in activity are analyzed. To start, the average activities belonging to the different measure categories are shown Table 24.

Table 24 - Average activity of a BPM based on their measure category

Measure category	Average activity	Number of measures
Bicycle demand	0.339	22
PT demand	0.450	10
Multimodal demand	0.651	1
General demand	0.280	9
Employer demand	0.231	6
Bicycle & PT demand	0.640	3

What can be seen from Table 24 is that the averages of the different measure categories differ quite a lot. There is namely more than a factor of two difference between the highest and lowest average activity. Although due to the lack in number of BPMs for certain categories, they are a little difficult to straight up compare them to each other.

To analyze if a certain measure category outperforms another measure category, z-tests are performed. All measure category datasets are complying to the Kolmogorov-Smirnov test, except for the multimodal transport measure category, due to this measure category only containing one BPM. The outcomes of the z-tests are shown in Table 25. When a measure category (horizontal) has a statistically significantly higher activity than another category (vertical), within a confidence interval of 80 percent, there is a plus present in the cell and a minus when they are statistically significantly lower, within that same confidence interval.

Table 25 – Comparing the activity between measure categories, outcomes z-tests

	Bicycle demand	PT demand	General demand	Employer demand	Bicycle & PT demand
Bicycle demand				+	-
PT demand			+	+	-
Multimodal demand					-
General demand		-			-
Employer demand	-	-			
Bicycle & PT demand	+	+	+	+	

What can be seen from Table 25 is that general demand measures are performing worse than public transport demand measures, employer demand measures are performing worse than both bicycle and PT demand measures and that bicycle & PT demand measures are performing better than all other BPMs.

The measure category that both incentivizes switching to cycling and public transport has a statistically significant higher activity compared to all other categories. This is something what also seems to work when packaging measures, see the outcomes from hypothesis 2.

Conclusions

When in search for the highest activity of participants in a BPMs, the BPM where both bicycle and public transport are incentivized is outperforming all other BPM categories. BPMs with just the incentive switch to public transport also have participants with a relatively high activity. These two measure categories could therefore be advantageous to choose when trying to achieve a high activity for participants by implementing a BPM on its own. Low performing measure categories are general incentives to decrease car use and employer-based BPMs. These measure categories lead to the lowest activity from the participants and could therefore be less advantageous to choose trying to achieve a high activity through independent BPMs.

6.3 Observed activity by region

Besides the impact of the measure category on the activity, there are also regional impact present on the activity. Similar as for the measure category there were also differences found in average activities between BPMs corresponding to the different regions. In this section, these differences in activity are analyzed. To start, the average activities belonging to the different regions are shown in Table 26. Note that the average activity embodies the totality of all impacts on the BPMs in the regions.

Table 26 - Average activity of a BPM based on their region

Region	Average activity	Number of measures
HGL	0.411	4
LWD	0.299	4
MAA	0.447	7
MNL	0.278	17
MRA	0.543	11
NBR	0.255	5
ZKN	0.161	3

What can be seen in Table 26 is that the average activity differs quite a bit. The region with the highest average activity, has an average activity that is more than three times that of the region with the lowest average activity. Although the lack in number of measures for a region can be a factor in the performance of that region, positive or negative.

To analyze if a certain region outperforms another region, z-tests are performed. All are complying to the Kolmogorov-Smirnov test. The outcomes of the z-tests are shown in Table 27. When a region (horizontal) has a statistically significantly higher activity than another region (vertical), within a confidence interval of 80 percent, there is a plus present in the cell and a minus when they are statistically significantly lower.

Table 27 - Comparing the activity between regions, outcomes z-tests

	HGL	LWD	MAA	MNL	MRA	NBR	ZKN
HGL							+
LWD			-		-		+
MAA		+		+		+	+
MNL			-		-		+
MRA		+		+		+	+
NBR			-		-		+
ZKN	-	-	-	-	-	-	

What can be seen from Table 27 is that both MAA and MRA have statistically significant higher activities than LWD, MNL, NBR and ZKN. Further are HGL, LWD, MNL and NBR also have statistically significant higher activities than ZKN. This means that ZKN has statistically significant lower activities than all the other regions.

Conclusions

Although the different regions have different magnitudes for activities in their BPMs and some have significantly higher activities than others, it is difficult to pinpoint the reasoning why this occurs. This is due to being an aggregate of all impacting factors on the BPMs in these regions. To sum up these are regional characteristics of the traffic network, process characteristics of the team implementing these measures, socio demographic characteristics of the region, TMP configuration factors and possibly other factors. What can be seen however is that Maastricht and Metropoolregio Amsterdam have a significantly higher activity than four of the six other regions and that all regions have a significantly higher activity than Zwolle-Kampen.

6.3.1 Quantifying some regional characteristics

In section 9.4.3 of the appendix, the impact of some regional characteristics on the activity of BPMs from BBV is quantified. This is done by performing a linear regression on these variables corresponding to the observed activity.

6.4 Quantifying impact factors on the activity

From the previous sections it can be seen that there were multiple factors impacting the performance of the activity of BPMs. The three overarching factors are packaging type, measure type and region in which the BPM is executed. To separate the impactof these factors a linear regression is performed. This will indicate the effect of the individual components on the activity of a BPM. For TMP configuraton, the components are there possible link to an IPM or to another BPM that incentivizes the switch to a different mode. For measure type, the components are all the different measure categories Finally, the components for the regions in which the BPM is executed are all participating regions. The outcomes of the linear regression are shown in Table 28. A visual representation of these outcomes is shown in Figure 7.

Table 28 – Quantifying the impact of TMP configuration, measure type and region on the activity of a BPM. Linear regression outcomes

Source	Value	Standard error	t	Pr > |t|	Lower bound (95%)	Upper bound (95%)
Intercept	0.150	0.269	0.559	0.580	-0.395	0.696
Link to infrastructure	0.179	0.135	1.330	0.192	-0.094	0.453
Multiple mode options	0.272	0.165	1.648	0.108	-0.063	0.607
Bicycle demand	-0.072	0.210	-0.341	0.735	-0.497	0.353
PT demand	-0.003	0.213	-0.016	0.987	-0.435	0.428
Multimodal demand	0.210	0.414	0.507	0.615	-0.629	1.049
General	0.029	0.247	0.119	0.906	-0.471	0.530
Employer	-0.026	0.258	-0.101	0.920	-0.550	0.498
Bicycle & PT demand	0.000	0.000				
HGL	0.044	0.246	0.180	0.858	-0.454	0.542
LWD	0.184	0.232	0.793	0.433	-0.286	0.654
MAA	0.111	0.240	0.464	0.645	-0.375	0.598
MNL	0.062	0.199	0.314	0.756	-0.341	0.466
MRA	0.157	0.240	0.656	0.516	-0.328	0.643
NBR	0.122	0.220	0.557	0.581	-0.323	0.568
ZKN	0.000	0.000				

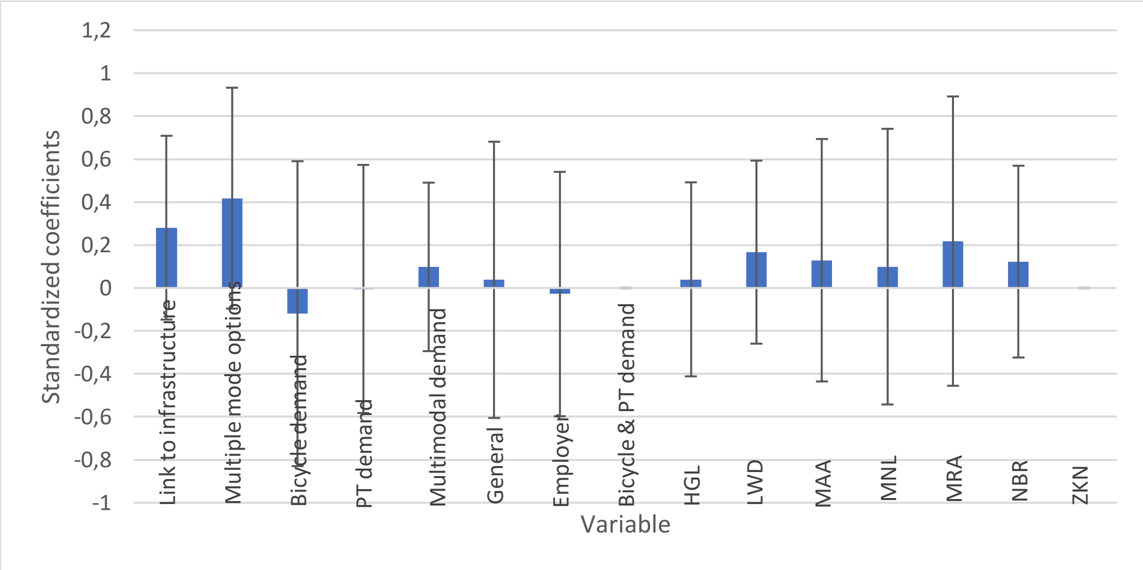

Figure 7 – Magnitude of impact of TMP configuration, measure type and region on the activity of a BPM (95% confidence interval)

Important to note is that all variables are binary, meaning that when they comply to the corresponding component a one is present and when they do not comply a zero is present. Note that the measure type and the regions in which the BPM is executed are dependent on each other, meaning that only one option can be chosen per BPM and all others are therefore not chosen. This leads to one variable from both factors to have a value of zero. All other values of the variables from these factors are relative to those variables. I.e. in Table 28 'Bicycle & PT demand' and ZKN are zero, meaning that when a 'Bicycle & PT demand' BPM would be executed in ZKN the expected activity would be 0.150 pa/pp (the intercept). If this BPM would have another measure type the value would change based on the corresponding variable value, the same holds for the different regions. Finally, the TMP configuration variables mean that if that BPM would have a link to an IPM, the activity would increase with 0.179 pa/pp and when multiple mode options would be available the activity would increase with 0.272 pa/pp.

Important to note is that the p-value of all variables, except for the TMP configuration components, is larger than 0.40. The p-values relates to the confidence interval in which variable is a good predictor for the activity. Having a p-value lower than 0.20 means that these variables are good predictors within a confidence interval of 80 percent. This only holds for the TMP configuration components. The other variables, all have p-values higher than 0.40 and are therefore bad predictors.

Due to all variables apart from the TMP configuration components, being bad predictors, a linear regression is performed on less variables as well. This is done for the TMP configuration with the measure type and for the TMP configuration with the regions. The results are shown in Table 44 and Table 45 in section 9.4.4 of the appendix. This however did not improve the predictive accuracy of these variables. Therefore, these are not used for a further analysis.

6.4.1 Magnitude of impact factors

The values of the variables of the TMP configuration components are respectively 0.179 pa/pp and 0.272 pa/pp, meaning that they both are bringing a positive value to the activity of a BPM, when the BPM is implemented in such a TMP configuration. When both links are present the added value would be 0.451 pa/pp. The values of the variables of measure type are between -0.072 pa/pp and

0.210 pa/pp, meaning that when choosing a measure category, a difference of 0.282 pa/pp can be made depending on the measure type. Where choosing bicycle demand has the lowest value and multimodal demand the highest. A similar scenario holds for region, here the variables are between 0.000 pa/pp and 0.184 pa/pp, meaning that the difference in region can be 0.184 pa/pp, depending on where the measure is executed. When implementing BPMs this can however most likely not be a choosing possibility, the region of implementation would depend on the location of the traffic problems that need to be tackled. A summation of the magnitude of the impact of the three different factors is given in Table 29.

Table 29 - Impact of the different factors

Impacting factor	Activity
TMP configuration	0.451
Measure type	0.282
Region	0.184

What can be seen from Table 29 is that the magnitude of the impact is highest for the TMP configuration, then the measure type and at last the region in which the measure is executed.

6.4.2 Conclusion

This section also indicates that there is indeed an impact of TMP configuration, measure type and region on the activity of a BPM. The impact of a measure type and a region however need to be unraveled further, due to their components being unreliable predictors. The impact of TMP configuration however is shown here, by having quite a large magnitude in comparison with the other components and being a good predictor of the activity, within a confidence interval of 80 percent. Having the largest magnitude of impact and also being the best predictor means that packaging has the largest impact on the activity of a BPM. This is followed by the measure type and then the region, although these are bad predictors as already been touched upon.

6.5 Conclusions

6.5.1 Main findings in testing the hypotheses

The main findings from the hypotheses testing are presented in Table 30. Here the level of statistically significant outcomes is presented, in whether the sub-sets contained higher or lower values than the compared sub-sets. In observation level 2a and 2b there are two outcomes per hypothesis. This is due to both sub-sets are compared to their expected average value instead of to each other. The first column contains the outcome from the sub-set not complying with the hypothesis and the second with the outcome of the sub-set complying with the hypothesis.

Table 30 - Main findings of testing the hypotheses over all observation levels

	Hypothesis 1: higher activity when interacting with an IPM?		**Hypothesis 2: higher activity when given multiple options to avoid peak?**	
Observation level 1	Possible, absolute z-value between 0.842 and 1.282.		Probable, absolute z-value higher than 1.645.	
Observation level 2a (category)	No statistically significant outcome.	No statistically significant outcome.	Probable, absolute t-value higher than 1.645.	Plausible, absolute t-value between 1.282 and 1.645.
Observation level 3a (category)	No statistically significant outcome.		Probable, absolute z-value higher than 1.645.	
Observation level 2b (region)	No statistically significant outcome.	Possible, absolute t-value between 0.842 and 1.282.	No statistically significant outcome.	No statistically significant outcome.
Observation level 3b (region)	Probable, absolute z-value higher than 1.645.		-	

6.5.2 Observed activity by measure category

There is quite a difference in activity between BPMs in different measure categories. The BPMs in the measure category where both bicycle demand and public transport demand are incentivized has the highest activity. This is in line with findings from testing the second hypothesis, where the activity is higher when participants are presented with multiple options to avoid peak. The second highest goes to BPMs in the category public transport. When composing TMPs these measure categories could be kept in mind, when aiming at a high activity for participants in BPMs.

6.5.3 Observed activity by region

There is also quite a difference in activity between BPMs in the different the regions. Metropool regio Amsterdam and Maastricht, have statistically significant higher activities in BPMs than four of the other regions. Due to this embodying all the impacting factors of the regions it is difficult to pinpoint the underlying nature of these activities in BPMs being higher in certain regions.

Contextual regional characteristics

There is a positive relation between the activity of participant in a region and the railroad density, the number of delayed rides and the number of movements per density in a region. There is also a negative relation between activity of participants in a region and the total road density, the motorway density and the bicycle path density. These relations could be used to roughly estimate the activity of a BPM, when a similar BPM has been performed in another region. These could also be used to see how these certain contextual regional characteristics impact the activity of participants of BPMs, based on data from this study.

6.5.4 Quantifying the impact factors on the activity

From TMP configuration, measure type and region, the largest impact on the activity of a BPM is the TMP configuration. This impact has the largest magnitude while also having the highest predictive accuracy. The measure type has the second highest impact followed by the region. The components of these two factors however were unreliable predictors, making it difficult to pinpoint the magnitude of their impact within a reasonable confidence interval.

7 Overall conclusions and recommendations

In this chapter the main findings, a discussion, political implications of this study and further research are presented. The main findings connect to the answers of the main research question and the sub-questions. The discussion will elaborate on the parts of this study which resulted into uncertainties in the conclusions. The political implications are then shown. The political implications are connected to the findings of this study. Lastly, the research that would be interesting to continue on after this study is discussed.

7.1 Main findings

To recap, the main research question was as follows:

How does a traffic measure package configuration impact the performance outputs of a behavioral policy measure in that traffic measure package?

Two TMP configurations containing a BPM have been analyzed when answering the main research question. These two configurations were a BPM interacting with an IPM that incentivizes the switch to the same alternative mode and a BPM interacting with another BPM that incentivizes the switch to a different alternative mode.

The performance outputs of the BPMs that have been analyzed were the degree of participation and the activity. The performance outputs are analyzed by two different datasets. The outcomes of those analyses are as follows.

It is likely that when a BPM interacts with an IPM that incentivizes a switch to the same alternative mode, that BPM would have a higher degree of participation than an independently implemented BPM. It is also possible that a BPM in such a TMP configuration has a higher activity than an average BPM. Due to both performance outputs being positively impacted by the TMP configuration, it is assumed that the effectiveness from such a BPM would also be positively impacted by such a configuration.

It is likely that when a BPM interacts with another BPM that incentivizes the switch to a different alternative mode, that BPM would have a lower degree of participation than an independently implemented BPM. It is however probable that a BPM in such a TMP configuration has a higher activity than an average BPM. Due to the degree of participation being negatively impacted and the activity being positively impacted by the TMP configuration it is not yet clear if the effectiveness of a BPM would be positively or negatively impacted by such a configuration.

7.2 Discussion

There is a level of uncertainty surrounding the main findings of this study. The main findings are based on the two hypotheses being tested, by analyzing two datasets. The level of uncertainty for the conclusions, who are based on the analysis of these two datasets, lies in the fact that the datasets were not obtained with the research questions of this study in mind. There were also other factors of impact on the performance outputs of the BPMs and the datasets were independent from each other. Because the datasets that are used to analyze the performance outputs of the BPMs were not compiled with the research questions of this study in mind, some assumptions had to be made to translate the outcomes of the questionnaire to answer the research questions. Having these assumptions present leads to uncertainty in the conclusions. Both datasets had contextual characteristics that impact the dataset. This also leads to uncertainty in the conclusions. The uncertainty of the other impacting factors is party negated by the size of both datasets. Due to both datasets being quite large the effect of other impacting contextual characteristics is mitigated. Another reason for uncertainty in the main findings is due to the fact that the datasets that were used are independent from each other. This makes it that their outcomes could not straightforward be added up with each other. This is partly mitigated by the fact that the datasets are both based on Dutch travelers from the same time period.

Not having these uncertainties would lead to clearer outcomes. Although it is likely that a dataset has some level of noise when this is based on policy measures who are implemented in real-life scenarios.

7.3 Main policy implications

When coming to policy implications from the findings from this research the main two are listed and elaborated here below.

First, coupling a BPM to incentivize car users to switch modes with an IPM to incentivize the same car users to switch to the same mode could likely increase the degree of participation, possibly increase the activity and therefore also likely increase the effectiveness of that BPM. This leads to:

- Accompany a BPM with an infrastructural improvement that incentivizes the switch to the same mode

Because there are car users that need to have an infrastructural improvement on top of a behavioral improvement to change their travel behavior. When these car users become participants in that BPM they are also likely to avoid peak more often based on the infrastructural improvement. It would therefore be of interest to support a BPM, with an infrastructural improvement to increase the performance outputs. It should be noted that the right combination of BPM and IPM should be found, because not all infrastructural improvements yield the same magnitude of increase in degree of participation.

Second, coupling a BPM to incentivize car users to switch modes with another BPM to incentivize the same car users to switch to a different mode probably increases the activity of that BPM. This leads to:

- Offering multiple options for the car users to avoid peak

Because when presenting car users with BPM with different incentives to avoid peak, they have the option to choose the BPM that suits their travel behavior the best. This makes the participants more active in avoiding peak. It would therefore a good idea to present participants of BPMs with multiple options to switch modes when wanting to increase their activity, compared to them only having a single option. A downside of such a TMP configuration is that combining these BPM is likely to lead to a lower degree of participation. Due to an negative impact on the degree of participation and a positive impact on the activity, the impact on the effectiveness of a BPM is still unclear. When it would be more important that participants achieve a higher number of peak avoidances than it would be to get as much participants as possible, this would be a good TMP configuration to implement.

7.4 Additional policy implications

7.4.1 Knowing the target audience

When packaging policy measures it is important to know the target audience that should be persuaded to avoid peak. The more there is known about the target audience the more of a tailored TMP can be composed to comply to the needs of that specific target audience. Car users could be more inclined to take part in a policy measure and participants could be more inclined to avoid peak more often. Some of the characteristics of a target audience that can be useful to know are:

- Commute distance
- Preferable mode to switch to
- Ability to switch to another mode
- Reasoning of wanting to avoid peak
- Reasoning of not wanting to participate in a policy measure

The more that there is known about the target audience the more of an in-depth analysis can be made on what types of BPMs could work best for that specific target audience and what combination of policy measures could increase the degree of participation, the activity and/or the effectiveness.

Because knowing the target audience completely is not a reasonable goal, giving the car users multiple options in avoiding peak could be a good alternative. This way the car users can choose the option that fits them best, resulting in a higher activity when they become a participant in the BPM. This relates back to the previous policy implication on the TMP configurations.

7.4.2 Knowing transportation network

While it is great to know more about the target audience, the transport network needs to be examined as well. This is to find out if car users are actually able or likely to switch to alternate modes or chose another route. When for instance the cycling network is underdeveloped towards a business area, it is less attractive for car users who work there to switch to cycling. A BPM aimed to increase the attractivity to switch to cycling could therefore not be a success. When the transportation network is not capable of supporting the incentive of a BPM, either an IPM should be implemented to negate that or another type of BPM should be taken to make these car users avoid peak.

Combining the knowledge of the target audience and the transportation network can lead to the best fitting TMP to be set up in a certain area.

7.4.3 Better and universal monitoring

This study was largely based on BPM data from the BBV program, which was a program that executed hundreds of policy measures in multiple regions throughout the Netherlands. The biggest advantage of doing a study on the BPMs in this program is that there were a lot of policy measures executed, meaning that there was a lot of data available afterwards. The downside of using this dataset as a base for the analysis is that not all BPMs were monitored in the same way, by each region. This led to an absence of the monitored number of reached target audience for most BPMs. Having this number, as well as the number of participants and the number of peak avoidances, would give a better insight in the workings of different TMPs. My recommendation therefore is to monitor these three outputs closely in future TMPs and in the same way throughout multiple projects. Having the same data from multiple TMPs can lead to more of an in-depth evaluation of policy measures in certain types of TMPs.

7.5 Further research

7.5.1 Dedicated policy measure studies

This study was mostly based on BPM data from the BBV program, which was a program that executed hundreds of policy measures in multiple regions throughout the Netherlands. The biggest advantage doing a study on the BPMs in this program is that there were a lot of measures executed, meaning that there was a lot of data available afterwards. The downside of performing an analysis on the data from the BBV program is that these BPMs were not executed with the research questions of this study in mind. This means that although there is a lot of data available, this data is not specifically aggregated for this study. That means that there was room for a noise in the data based in the impact of contextual characteristics. My recommendation therefore is, when wanting to get a more accurate understanding on the workings of performance outputs specifically impacted by TMP configuration. Or when wanting to accurately want to research the impact of another factor on the performance of policy measures, BPMs should be implemented with set research questions in advance.

In this program multiple different BPMs were implemented in different regions. This makes it difficult to fairly compare the outcomes of these BPMs to each other. The different impacts on the outputs of these BPMs makes it also difficult to extract the impact of the configuration of the TMP. This makes it that the hypotheses could not be tested exclusively using these impacts. There were always other outside factors of impact on these outcomes as well. This could be combated by implementing similar policy measures with the same execution plan, in the same region. This would create more of a unity between the executed measures, which would make the comparison between them fairer. It would essentially be the intention to create a context where most of the other impacting factors are the same or at least similar. However, restricting the impact of other factors on the policy measures could be hard to achieve and it is likely not possible to create completely similar scenarios in which these policy measures can be implemented. This is due to policy measures being implemented in the real world with everchanging contextual characteristics. This could be combated by more research on the impact of other factors on policy measures or by creating a theoretical environment to test the impact of composition of policy measures. When this is tested theoretical, the circumstances can be regulated, opposed to in a real-life scenario.

7.5.2 Study the TMP configurational impact on more performance outputs

In this study the impact of TMP configuration on the activity of a BPM was studied using BPM data from BBV. The degree of participation was analyzed using different independent dataset from a travel behavior revealed preference questionnaire. To get better insight into the workings of a BPM, it would be better if both performance outputs were known for the one dataset. Having both of the performance outputs also means that the effectiveness is known. All three together give more of a complete image of the performance of a BPM. To get this better image the number of reached target audience, the number of participants and the number of peak avoidances should be known.

7.5.3 Study the context in which a policy measure is implemented

In this study, using BPM data from BBV, the activity of participants from BPMs was investigated in certain configurations of a TMP. However, this was not the only impact on the performance outputs of a policy measure. Policy measures are also impacted by the context in which they are executed. This context can consist of the regional, process or socio-demographic characteristics as well as the type of policy measure that is executed. In a linear regression in section 6.5.4, the measure category type and region all had bad predictors, meaning that their impact could not be accurately determined using this dataset. It could therefore be of interest to research the magnitude of the impact of other factors on a policy measure. Knowing if these factors are positively or negatively influencing the performance of a policy measure could be very useful when composing policy measures in future projects.

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9 Appendix

In the appendix extra information is added which support the main text. These can consist of text, tables or figures. The layout is structured as such that the titles of the sections of the appendix correspond to the chapters of the main text of which the content is supportive to.

9.1 Addition to chapter 2

In this section of the appendix two tables are added showing the initial dataset and the used dataset from BBV containing BPMs with some of their descriptions and outputs. Then the elaboration of three tests is added. These tests are the two sample z-test, the Kolmogorov-Smirnov test and the one sample t-test. These tests are part of the research method and used for the data analysis of BPM data obtained from BBV.

Table 31 – Initial dataset containing BPMs from BBV

Code	Name measure	Name sub-measure	Measure category	Reached target audience	Participants	Peak avoidances
LWD-BBV-003.	Spitsmijdend parkeren	Spitsmijdend parkeren	General demand	1935	174	120
MAA-BBV-003-004 .	Slim werken	Slim werken	Employer demand	-	2737	1244
MNL.BBV.504f	U15 plan	Flexwerken	Employer demand	-	2144	229
MNL.BBV.504g	U15 plan	Thuiswerken	Employer demand	-	2146	249
MNL.BBV.504h	U15 plan	Andere vestiging	Employer demand	-	1273	116
MNL.BBV.504i	U15 plan	Reiskostenvergoeding Auto	General demand	-	863	173
MNL.BBV.504k	U15 plan	Parkeertarieven WG	General demand	-	884	85
MNL.BBV.504l	U15 plan	Beschikbaarheid parkeren WG	General demand	-	3727	316
MNL.BBV.510.	Spitsmijden Galecopperbrug vervolg	Spitsmijden A12 Utrecht (vh. Spitsmijden Galecopperbrug vervolg)	General demand	-	6111	1900
MRA-BBV-201.	Spitsmijden A27 Almere-Utrecht	Spitsmijden. A27 deel beter benutten	General demand	39775	1519	260
NBR-BBV-006d	Breda Corridor Noord en Zuid	Singelmijden Wilhelminasingel	General demand	7209	228	58
NBR-BBV-010.	Spitsmijden A2	Spitsmijden A2	General demand	11976	2676	868.8
MNL.BBV.521.	Gebiedsgericht Spitsmijden	Gebiedsgericht Spitsmijden	General demand	-	3670	1414.5

HGL-BBV-001d	Projecten	E-biketool (SP)	Bicycle demand	-	111	19
LWD-BBV-002b	Leeuwarden op de fiets	Rij2Op5	Bicycle demand	7095	1490	158
LWD-BBV-002d	Leeuwarden op de fiets	E-bike met korting	Bicycle demand	4945	890	91
MAA-BBV-023.	Onderwijsaanpak	Onderwijsaanpak	PT demand	661	41	8
NBR-BBV-002a	Fietsbeleid 2.0: Ons Brabant fietst	B-Riders	Bicycle demand	-	5775	2406
NBR-BBV-002b	Fietsbeleid 2.0: Ons Brabant fietst	Employer demandsaanpak fiets	Bicycle demand	-	2573	686
NBR-BBV-005.	OV marketing	We Bussen	PT demand	1869	718	10
ZKN-BBV-007-009a	Fietsprojecten Zwolle Kampen	Fietsstimulering (fase 1)	Bicycle demand	-	1077	125
ZKN-BBV-011a	De Overstap	Nieuwe medewerkerspas	PT demand	-	226	45
MAA-BBV-001.	Fietsimpuls	Fietsimpuls	Bicycle demand	14650	5297	1990
MAA-BBV-005.	OV impuls	OV impuls	PT demand	-	1133	720
MAA-BBV-021a	Regioregie 2.0	Fietsacties	Bicycle demand	-	1579	609
MAA-BBV-021b	Regioregie 2.0	OV acties	PT demand	-	2022	876
MRA-BBV-111b	Zuidas	Reizen buiten de spits	PT demand	-	252	34
MRA-BBV-112.	Mobiliteitsloket AMC	Mobiliteitsloket AMC	Bicycle and PT demand	-	400	280
MRA-BBV-113.	Programma Rieker & Amstel Businesspark	Programma Rieker & Amstel Businesspark	Bicycle and PT demand	-	337	331
MRA-BBV-113a	Programma Rieker & Amstel Businesspark	Aanpassen besloten vervoerssysteem	PT demand	-	185	296
MRA-BBV-113b	Programma Rieker & Amstel Businesspark	Pilot E-bikes	Bicycle demand	-	109	8
MRA-BBV-113c	Programma Rieker & Amstel Businesspark	Pilot Filesporten	Employer demand	-	22	7
MRA-BBV-113d	Programma Rieker & Amstel Businesspark	Pilot Deelfietsen	Bicycle demand	-	21	20
MRA-BBV-911c	Bereikbaarheidsplan IJmond Bereikbaar	OV-stimulering	PT demand	-	50	17

MRA-BBV-912.	OV en Fietsimpuls Waarderpolder	OV en Fietsimpuls Waarderpolder	Bicycle and PT demand	6586	418	200
MAA-BBV-024d	Parkeren Maastricht	B1 Ervaaraanbod	Bicycle and PT demand	-	129	84
HGL-BBV-001b	Projecten	DB+	Bicycle demand	-	35	8
MNL.BBV.204	Aanleg pechhavens A28	Samengevoegd	PT demand	2450	637	419
MNL.BBV.504j	U15 plan	Reiskostenvergoeding Fiets	Bicycle demand	-	398	58
MNL.BBV.511.	Fietsimpuls	Fietsimpuls	Bicycle demand	-	2743	318
MNL.BBV.512.	E-bike	E-bike	Bicycle demand	-	57	53
MNL.BBV.515.	Scholenaanpak	Scholenaanpak	Bicycle demand	16000	526	186
MNL.BBV.522a	De Gebruiker Centraal	Lekker Lopen, Fijn Fietsen	Bicycle demand	-	575	208
MNL.BBV.522b	De Gebruiker Centraal	Kindje onderweg	Bicycle demand	-	607	73
MNL.BBV.522c	De Gebruiker Centraal	Fietskaart voor nieuwe inwoners	Bicycle demand	-	336	170
MNL.BBV.522d	De Gebruiker Centraal	Juffen en Meesters op de e-bike	Bicycle demand	-	11	1.6
ZKN-BBV-007-009a	Fietsprojecten Zwolle Kampen	Fietsstimulering (fase 2)	Bicycle demand	-	568	96
HGL-BBV-		OV-probeerpas	PT demand	12018	1322	380
HGL-BBV-001a	Projecten	KNMP	Bicycle demand	-	68	65
MRA-BBV-911.	Bereikbaarheidsplan IJmond Bereikbaar	Bereikbaarheidsplan IJmond Bereikbaar	Bicycle and PT demand	-	2700	2000
MRA-BBV-911b	Bereikbaarheidsplan IJmond Bereikbaar	Fiets vraag	Bicycle demand	-	1800	833

Table 32 – Adjusted dataset used for the analysis, containing BPMs from BBV

Code	Name measure	Name sub-measure	Measure category	Link with IPM	Bicycle and PT	Activity
LWD-BBV-003.	Spitsmijdend parkeren	Spitsmijdend parkeren	General demand	0	0	0.689655
MAA-BBV-003-004 .	Slim werken	Slim werken	Employer demand	0	0	0.454512
MNL.BBV.504f	U15 plan	Flexwerken	Employer demand	0	0	0.10681
MNL.BBV.504g	U15 plan	Thuiswerken	Employer demand	0	0	0.11603
MNL.BBV.504h	U15 plan	Andere vestiging	Employer demand	0	0	0.091123
MNL.BBV.504i	U15 plan	Reiskostenvergoeding Auto	General demand	0	0	0.200463
MNL.BBV.504k	U15 plan	Parkeertarieven WG	General demand	0	0	0.096154
MNL.BBV.504l	U15 plan	Beschikbaarheid parkeren WG	General demand	0	0	0.084787
MNL.BBV.510.	Spitsmijden Galecopperbrug vervolg	Spitsmijden A12 Utrecht (vh. Spitsmijden Galecopperbrug vervolg)	General demand	0	0	0.310915
MRA-BBV-201.	Spitsmijden A27 Almere-Utrecht	Spitsmijden. A27 deel beter benutten	General demand	0	0	0.171165
NBR-BBV-006d	Breda Corridor Noord en Zuid	Singelmijden Wilhelminasingel	General demand	0	0	0.254386
NBR-BBV-010.	Spitsmijden A2	Spitsmijden A2	General demand	0	0	0.324664
MNL.BBV.521.	Gebiedsgericht Spitsmijden	Gebiedsgericht Spitsmijden	General demand	0	0	0.385422
HGL-BBV-001d	Projecten	E-biketool (SP)	Bicycle demand	0	0	0.171171
LWD-BBV-002b	Leeuwarden op de fiets	Rij2Op5	Bicycle demand	0	0	0.10604
LWD-BBV-002d	Leeuwarden op de fiets	E-bike met korting	Bicycle demand	0	0	0.102247
MAA-BBV-023.	Onderwijsaanpak	Onderwijsaanpak	PT demand	0	0	0.195122
NBR-BBV-002a	Fietsbeleid 2.0: Ons Brabant fietst	B-Riders	Bicycle demand	0	0	0.416623
NBR-BBV-002b	Fietsbeleid 2.0: Ons Brabant fietst	Employer demandsaanpak fiets	Bicycle demand	0	0	0.266615
NBR-BBV-005.	OV marketing	We Bussen	PT demand	0	0	0.013928

ZKN-BBV-007-009a	Fietsprojecten Zwolle Kampen	Fietsstimulering (fase 1)	Bicycle demand	0	0	0.116063
ZKN-BBV-011a	De Overstap	Nieuwe medewerkerspas	PT demand	0	0	0.199115
MAA-BBV-001.	Fietsimpuls	Fietsimpuls	Bicycle demand	0	1	0.375684
MAA-BBV-005.	OV impuls	OV impuls	PT demand	0	1	0.635481
MAA-BBV-021a	Regioregie 2.0	Fietsacties	Bicycle demand	0	1	0.385687
MAA-BBV-021b	Regioregie 2.0	OV acties	PT demand	0	1	0.433234
MRA-BBV-111b	Zuidas	Reizen buiten de spits	PT demand	0	1	0.134921
MRA-BBV-112.	Mobiliteitsloket AMC	Mobiliteitsloket AMC	Bicycle and PT demand	0	1	0.7
MRA-BBV-113.	Programma Rieker & Amstel Businesspark	Programma Rieker & Amstel Businesspark	Bicycle and PT demand	0	1	0.982196
MRA-BBV-113a	Programma Rieker & Amstel Businesspark	Aanpassen besloten vervoerssysteem	PT demand	0	1	1.6
MRA-BBV-113b	Programma Rieker & Amstel Businesspark	Pilot E-bikes	Bicycle demand	0	1	0.073394
MRA-BBV-113c	Programma Rieker & Amstel Businesspark	Pilot Filesporten	Employe r demand	0	1	0.318182
MRA-BBV-113d	Programma Rieker & Amstel Businesspark	Pilot Deelfietsen	Bicycle demand	0	1	0.952381
MRA-BBV-911c	Bereikbaarheidspla n IJmond Bereikbaar	OV-stimulering	PT demand	0	1	0.34
MRA-BBV-912.	OV en Fietsimpuls Waarderpolder	OV en Fietsimpuls Waarderpolder	Bicycle and PT demand	0	1	0.478469
MAA-BBV-024d	Parkeren Maastricht	B1 Ervaaraanbod	Bicycle and PT demand	1	1	0.651163
HGL-BBV-001b	Projecten	DB+	Bicycle demand	1	0	0.228571
MNL.BBV.204	Aanleg pechhavens A28	Samengevoegd	PT demand	1	0	0.657771
MNL.BBV.504j	U15 plan	Reiskostenvergoedin g Fiets	Bicycle demand	1	0	0.145729
MNL.BBV.511.	Fietsimpuls	Fietsimpuls	Bicycle demand	1	0	0.115931
MNL.BBV.512.	E-bike	E-bike	Bicycle demand	1	0	0.929825

MNL.BBV.515.	Scholenaanpak	Scholenaanpak	Bicycle demand	1	0	0.353612
MNL.BBV.522 a	De Gebruiker Centraal	Lekker Lopen, Fijn Fietsen	Bicycle demand	1	0	0.361739
MNL.BBV.522 b	De Gebruiker Centraal	Kindje onderweg	Bicycle demand	1	0	0.120264
MNL.BBV.522 c	De Gebruiker Centraal	Fietskaart voor nieuwe inwoners	Bicycle demand	1	0	0.505952
MNL.BBV.522 d	De Gebruiker Centraal	Juffen en Meesters op de e-bike	Bicycle demand	1	0	0.145455
ZKN-BBV-007-009a	Fietsprojecten Zwolle Kampen	Fietsstimulering (fase 2)	Bicycle demand	1	0	0.169014
HGL-BBV-		OV-probeerpas	PT demand	1	1	0.287443
HGL-BBV-001a	Projecten	KNMP	Bicycle demand	1	1	0.955882
MRA-BBV-911.	Bereikbaarheidsplan IJmond Bereikbaar	Bereikbaarheidsplan IJmond Bereikbaar	Bicycle and PT demand	1	1	0.740741
MRA-BBV-911b	Bereikbaarheidsplan IJmond Bereikbaar	Fiets vraag	Bicycle demand	1	1	0.462778

9.1.1 Two sample z-test

A z-test is a statistical test used to determine whether two population means are different. In this case, it is used to see if one population is statistically significantly larger than the other. This is used to find statistically quantitative relation between the split in the dataset that complies to the hypothesis or not. For the two populations the variance should be known, the sample sizes should be large, and they need to have a normal distribution. If the population has a normal distribution is determined using the Kolmogorov-Smirnov test. A z-test is similar to a t-test. The difference is that for a z-test the variance of the populations should be known and the size of the population should be larger. The z-test is best used with greater than 30 samples, because when the number of samples gets larger, the samples are considered approximately normally distributed. When the z-test is performed, the null and alternative hypotheses should be stated, next to the alpha and the z-score. The null hypothesis will be that both sub-sets are equal to each other. The alternative hypothesis will be that one is greater than the other (one sided). The alpha is the level of statistical significance of which the hypotheses need to comply. Here there is chosen for three levels, of significance corresponding to three alphas: 0.05, 0.10 and 0.20. When it complies to 0.05 the outcome can be considered as probable. When it complies to 0.10 and not 0.05 it can be considered as plausible that this outcome is true. When it complies to 0.20 and not to 0.10 it can be considered as possible that the outcome is true. When considering a one-sided z-test, which is used because the hypotheses that are investigated state that one group scores better than the other, the alpha value is linked to critical t-values. These are given in the table here below. The underlying reason why three levels of significance are chosen instead of one is to give a better view of the outcomes of the statistical tests. When only one level of significance is chosen the test is either passed or not. When dealing with this kind of data it would be more insightful to categorize the levels of significance in probable, plausible and possible. These are also seen in the table linked to their critical values.

Table 33 - Statistical significant confidence interval values

Confidence level	Alpha	Critical value (one sided)	Statement
0.95	0.05	1.645	Probable
0.90	0.10	1.282	Plausible
0.80	0.20	0.842	Possible

If the absolute value of the z-score, the outcome of the z-test, is higher that the critical value, the outcome of the test is statistically significant for the corresponding confidence level. In this case will the z-score be compared to the three critical values from the table above and when higher than 1.645 the outcome will be probable, when between 1.282 and 1.645 the outcome will be plausible and when between 0.842 and 1.282 the outcome will be possible. When the absolute value of the z-score is below 0.842 the outcome will be considered as statistically insignificant and no statement can be made on that outcome. The sign of the z-score is also important to note, when this is positive the average of the first sub-set will be larger than the that of the second and when this is negative it is the other way around.

9.1.2 Kolmogorov-Smirnov test

A criterion of using the z-test is that the dataset should have a normal distribution. This is being tested by performing the Kolmogorov-Smirnov test. This test is performed on both sub-sets of the data, separately, which are being used to test the hypothesis with. There are two Kolmogorov-Smirnov tests, a one sample test and an independent samples test. Here the one sample test is used, in which a sample is tested if it follows a given distribution, in this case a normal distribution. To compute the score of this test, the observed versus the expected cumulative relative frequencies are computed first, where the expected cumulative frequencies follow a normal distribution. Then the differences between the two are calculated for each sample. In order to being classified as a normal distribution the maximum difference will be compared to a critical value, obtained from a table based on a certain alpha and the number of data points. If this maximum absolute difference is lower that the critical value, the dataset is presumed to have a normal distribution.

9.1.3 One sample t-test

The one sample t-test is used to find out if the sub-sets are statistically higher or lower than the expected values calculated by the averages of the categories or regions. This is, just like the z-test, used to find statistical quantitative relations. This time between the data from the sub-sets and the expected values of the averages. Here the sample of observations should be larger or smaller than that specific mean. The statistical significance that is being used in this test is the same as for the z-test. Meaning that the same alpha values are used, which lead to the same critical t-values and the same three statistically significant statements as mentioned in table 1. Here the outcome will be compared to these values, which makes the process of interpreting the results the same as for the z-test. When performing this test, the samples should have a normal distribution, which is being tested by performing the Kolmogorov-Smirnov test.

9.2 Addition to chapter 3

In this section three figures are added. These are conceptual frameworks contain impacting factors on the performance of policy measures.

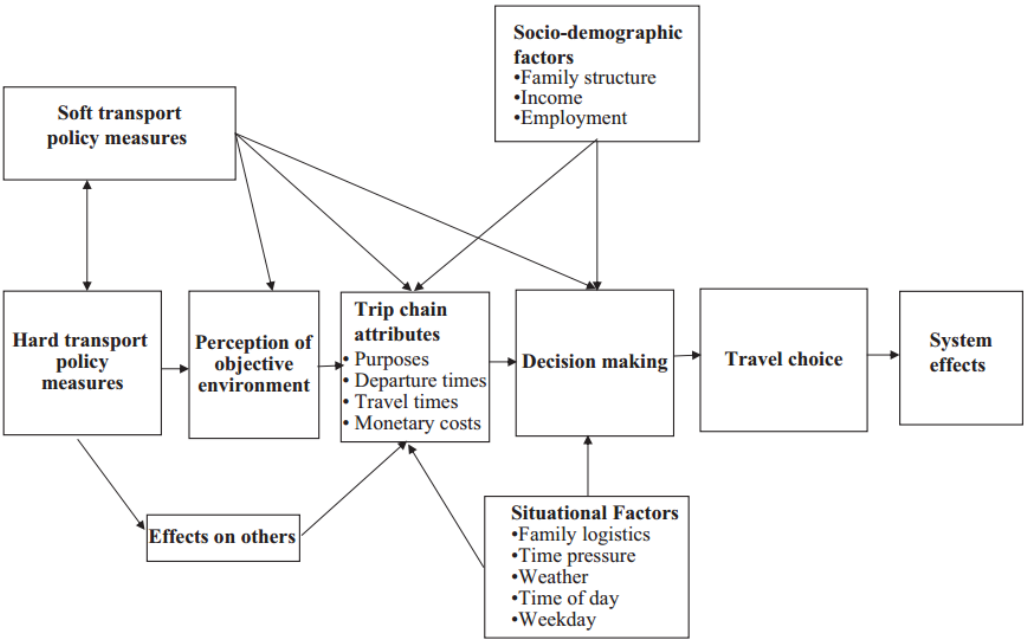

Figure 8 – General conceptual framework. Obtained from Bramberg et al., (2011)

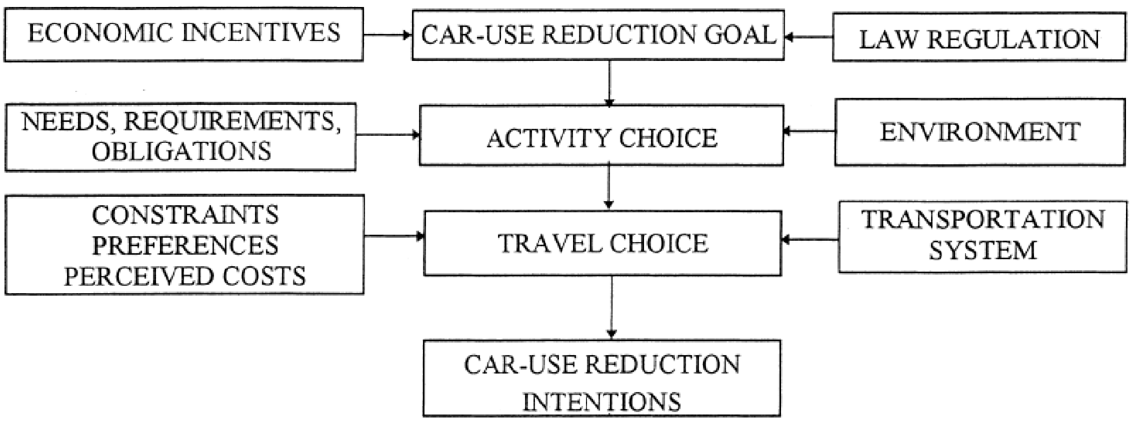

Figure 9 - Conceptual framework, determinants of car-use reduction intentions. Obtained from Gärling et al., (2000)

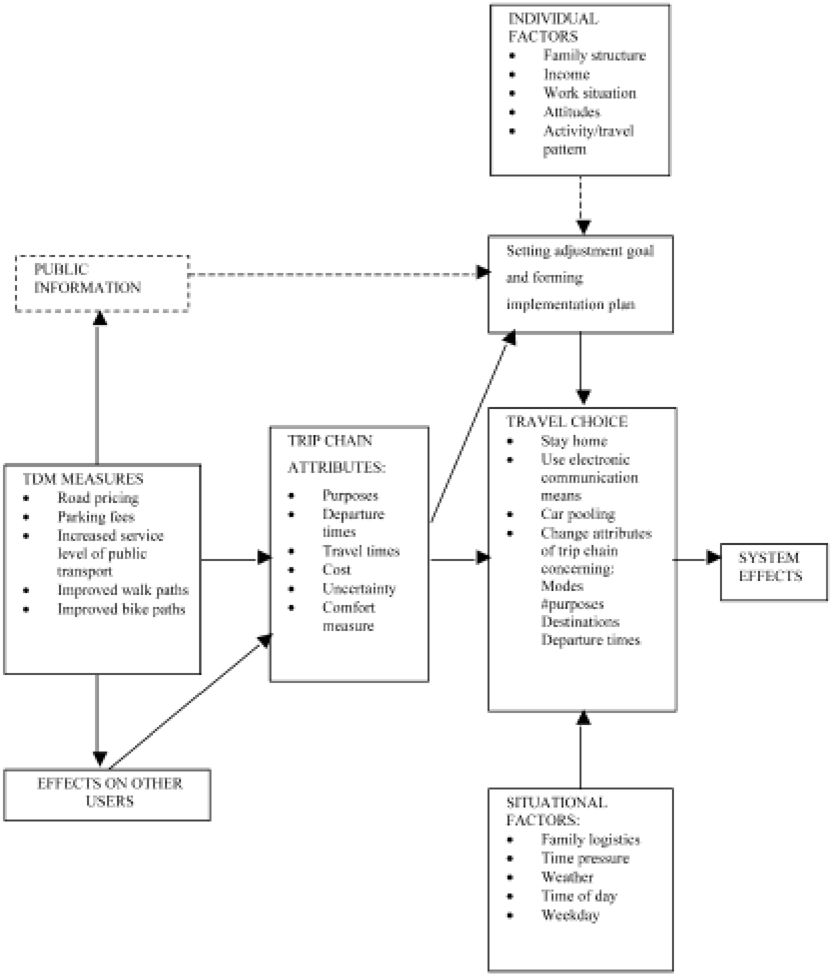

Figure 10 – Proposed conceptual framework. Obtained from Gärling et al., (2002)

9.3 Addition to chapter 5

In this section thee Venn-diagrams are shown. These show the percentage of car users that selected the combinations of infrastructural improvements on top of a single behavioral improvement to reduce their car use. There are also two tables present showing the extra percentage of car users selecting combinations of public transport travel improvements. The last table shows the Improved public transport travel possibilities chosen in combination and separately.

Bicycle travel improvement - Better bicycle sharing system

This Venn-diagram shows the extra percentage of car users that selected the combination of infrastructural improvements on top of having better bicycle sharing system. Overlapping circles indicate a combination of multiple infrastructural improvements. The blue numbers in the circles indicate the specific infrastructural improvement.

1. More parking spaces at employer
2. Better parking spaces at residence or station
3. Infrastructure has improved

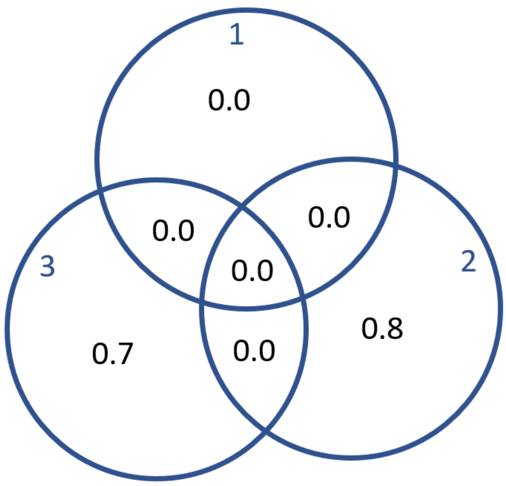

Figure 11 - Venn-diagram of additional percentages of car users reducing their car use, due to the combination of infrastructural improvements on top of having a better bicycle sharing system

Public transport improvement – Shorter travel time

This Venn-diagram shows the extra percentage of car users that selected the combination of infrastructural improvements on top of having a shorter travel time. Overlapping circles indicate a combination of multiple infrastructural improvements. The blue numbers in the circles indicate the specific infrastructural improvement.

4. Improved connection
5. More options
6. Shorter walking distance
7. More P+R options

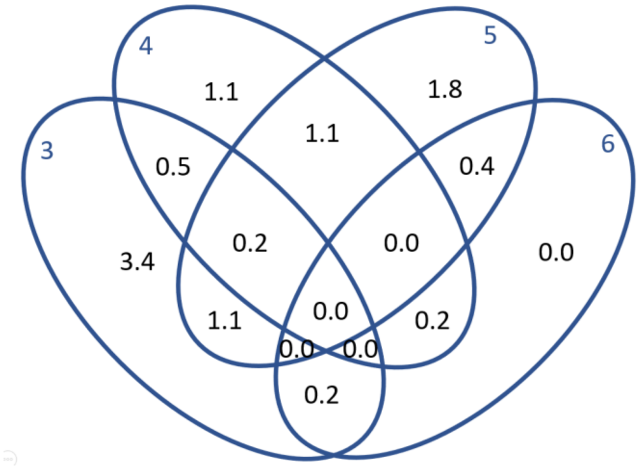

Figure 12 - Venn-diagram of additional percentages of car users reducing their car use, due to the combination of infrastructural improvements on top of having a shorter travel time

Public transport improvement – Higher frequency

This Venn-diagram shows the extra percentage of car users that selected the combination of infrastructural improvements on top of having a higher frequency. Overlapping circles indicate a combination of multiple infrastructural improvements. The blue numbers in the circles indicate the specific infrastructural improvement.

1. Improved connection
2. More options
3. Shorter walking distance
4. More P+R options

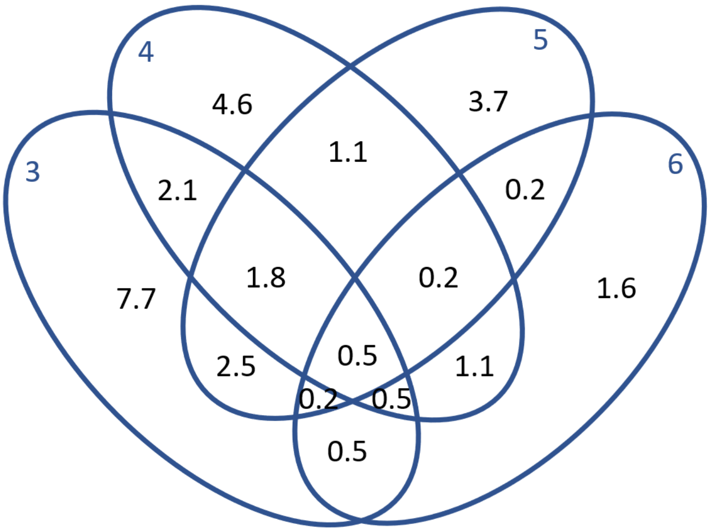

Figure 13 - Venn-diagram of additional percentages of car users reducing their car use, due to the combination of infrastructural improvements on top of having a higher frequency

Table 34 – Improved public transport travel possibilities chosen in combination and separately

Nr.	Answer possibility	Separately	Combination
1	Shorter travel time	16.1	83.9
2	Higher frequency	22.4	77.6
3	Improved connection	17.9	82.1
4	More options	17.4	82.6
5	Shorter walking distance	17.6	82.4
6	More P+R options	18.5	81.5

9.4 Additional data chapter 6

In this section some tables are shown together with some accompanying text explaining how the expected average activity of the analyzed groups is calculated. This is based on the composition of the group in measure category or region. This section also contains the quantification of some regional characteristics. It ends with Quantifying impact factors of BPMs. This is done by performing a linear regression.

9.4.1 Confounding the interaction impact of IPM on the activity of BPM (hypothesis 1)

Observation level 2a: Analysis based on expected values from measure categories

In the Table 35, this composition of the groups in measure category can be seen, together with the average activity of these measure categories over the entire BBV program.

Table 35 - Composition of the two groups, based their measure category

Measure category	Without IPMs	With IPMs	Average activity
Bicycle	10	12	0.339
PT	8	2	0.450
Multimodal transport	0	1	0.651
General	9	0	0.280
Employer based	6	0	0.231
Bicycle & PT	2	1	0.640

The expected average values for both groups are shown in Table 36. This is shown together with the actual average value, the absolute and relative difference.

Table 36 – Expected values, based on the composition of the two groups in measure category

Sub-set	Actual average	Expected average	Difference (abs)	Difference (rel)
Without infra	0.331	0.348	-0.017	-4.89%
With infra	0.427	0.391	+0.036	+9.21%

What can be seen from Table 36 is that the relative difference between the expected average value and the actual average value not that high, being 5 and 9 percent. This could indicate that being linked to IPMs or not impacts the activity of participants, but not that much when eliminating the measure categorial composition of the sub-sets.

Observation level 2b: Analysis based on expected values from regions

In

Table 37 here below the composition in region is given for the measures in the groups, together with the average activity from a measure in that region. Note that the average activity embodies the performance of off all BPMs in that region as a whole, based on this dataset. It represents regional, process and socio-demographic characteristics as well as the TMP composition. It does therefore not mean that one region outperforms another is the average activity is higher. It is namely including many factors that played a role on the performance of these BPMs.

Table 37 - Composition of the two groups, based their region

Region	Without IPMs	With IPMs	Average activity
HGL	1	3	0.411
LWD	4	0	0.299
MAA	6	1	0.447
MNL	8	9	0.278
MRA	9	2	0.543
NBR	5	0	0.255
ZKN	2	1	0.161

The expected average values for both groups are shown in Table 38. These are calculated similar to the expected average values based on the measure categories. This is shown together with the actual average value, the absolute and relative difference.

Table 38 – Expected values, based on the composition of the two groups in region

Sub-set	Actual average	Expected average	Difference (abs)	Difference (rel)
Without infra	0.331	0.371	-0.040	-12.1%
With infra	0.427	0.339	+0.088	+20.5%

What can be seen from the Table 38 is that the relative difference between the expected average value and the actual average value is somewhat high, being 12 and 20 percent. This could indicate that being linked to infrastructural policy measures or not impacts the activity of participants. Namely, when behavioral policy measures are not linked to those, they perform worse than expected and when they are linked to those, they perform better than expected. This when 'eliminating' the regional averages.

9.4.2 Confounding the interaction impact of a different BPM on the activity of BPM (hypothesis 2)

Observation level 2a: Analysis based on expected values from measure categories

In Table 39, the composition in measure category can be seen, together with the average activity of participants partaking in these measure categories, over the entire BBV program.

Table 39 - Composition of the two groups, based their measure category

Measure category	Single option	Multiple options	Average activity
Bicycle	16	6	0.339
PT	4	6	0.450
Multimodal transport	0	0	0.651
General	0	0	0.280
Employer based	0	0	0.231
Bicycle & PT	0	3	0.640

The expected average values for both groups are shown in Table 40. This is shown together with the actual average value, the absolute and relative difference.

Table 40 - Expected values, based on the composition of the two groups in measure category

Sub-set	Actual average	Expected average	Difference (abs)	Difference (rel)
Single option	0.266	0.361	-0.095	-26.4%
Multiple options	0.570	0.443	+0.127	+28.6%

What can be seen from Table 40 is that the relative difference between the expected average value and the actual average value is quite high, being 26 and 29 percent. This could indicate that having multiple options to avoid peak impacts the activity of participants while taking the composition of the sub-sets into measure category into account.

Observation level 2b: Analysis at level of region

Table 41 - Composition of the two groups, based their region

Region	Single option	Multiple options	Average activity
HGL	2	2	0.411
LWD	2	0	0.299
MAA	1	4	0.447
MNL	9	0	0.278
MRA	0	9	0.543
NBR	3	0	0.255
ZKN	3	0	0.161

The expected average values for both groups are shown here below. These are calculated similar to the expected average values based on the measure categories. This is shown together with the actual average value, the absolute and relative difference.

Table 42 - Expected values, based on the composition of the two groups in region

Sub-set	Actual average	Expected average	Difference (abs)	Difference (rel)
Single option	0.266	0.298	-0.032	-10.6%
Multiple options	0.570	0.528	+0.042	+7.97%

What can be seen from Table 42 is that the relative difference between the expected average and the actual average is somewhat high, being 11 and 8 percent. This could indicate that being linked to another BPM that incentivized switching to a difference mode increases activity despite regional factors.

9.4.3 Quantifying some contextual regional characteristics

Contextual regional characteristics can be used to help understand why BPMs in a certain region might have a higher activity than in others. Meaning why participants of BPMs in a certain area would be inclined to avoid peak hours more than in others, due to these characteristics. These regional characteristics namely describe two aspects of the traffic system. These two aspects are the 'level of service' and the 'push' factors in that traffic system. With 'the level of service', the supply side of the traffic system is described. Here the alternative options to driving through bottleneck are mapped out. Meaning that when the 'level of service' in a region would be relatively high, the participant has more options to avoid peak hour and can therefore achieve a higher activity in avoiding peak hours than when this would be relatively low. The other aspects are the 'push' factors, these describe the side hindrance side of the traffic system that car users experience. This can best be described in delay time. Here the thought is that when in a region the 'push' factors are relatively high, the participants experience more hinderance and are therefore more benefitted to avoid peak. This would suggest that their activity to avoid peak would be higher than when these push factors would be lower.

The following contextual regional characteristics are chosen to resemble the state of the traffic system. These characteristics however do not resemble the traffic system entirely. Partly, due to dependency of data, these are characteristics are chosen. But it must be kept in mind that these are mere gross indicators, which is also how they will be used in the analysis and the interpretation of the performance of the BPMs due to these regional characteristics. When regional characteristics are chosen that lead to a better representation of the traffic system, a more accurate estimation could be made on the impact of regional characteristics on the activity of BPMs. Some regional characteristics that could be thought of are: station density, vehicle hours delay, congestion severity index and travel costs for different modes. The regional characteristics that are chosen are listed here below and elaborated after that.

1.	Total road density	Level of service	(province)
2.	Motorway density	Level of service	(province)
3.	Railroad density	Level of service	(province)
4.	Bicycle path density	Level of service	(province)
5.	Number of delayed rides	Push factor	(province)

Total road density is chosen as a characteristic, because this describes the robustness of the car/traffic network. The values that are used are based on the total road density for the province in which the region lies, obtained from CBS for the year of 2017. When this is relatively high, car users could have multiple options to reach their destination. It could therefore be easier for them to travel by taking a detour around a bottleneck. This means that it could therefore also be easier to avoid peak hours on certain bottlenecks by still travelling by car. While this could be positive for avoiding peak hours at a certain bottleneck, this could be detrimental to car usage reduction in general. Because the car is more attractive when multiple routes are possible, switching to an alternative mode could be less attractive.

The characteristic motorway density is chosen similar to total road density. This characteristic is however specifically chosen because most bottlenecks in the BBV program are located at motorways. The values that are used are based on the motorway density for the province in which the region lies, obtained from CBS 2017. A relatively high motorway density entails that a car user has more options to choose from, when travelling over motorways. This could, similarly as for total road density, mean that avoiding these bottlenecks during peak hours could be more attractive to do by choosing a different route. Which on its turn could mean that switching to an alternative mode would become relatively less attractive. This could result in policy measures aimed at car users to switch mode to be less effective.

Choosing railroad density as a characteristic is because this describes the robustness of the train network. The values that are used are based on the railroad density for the province in which the region lies, obtained from CBS 2017. When this is relatively high, travelers could reach more destinations when travelling by train and the train could be easier to access in that region. It could also entail that there are more direct routes to reach a destination, which could entail a shorter travel time. This makes travelling by train a more attractive mode in that region. This could mean that when car users switch mode in this region, they are likely to travel more by train due to the ‘good’ infrastructure, in comparison to participants in regions with a low railroad density. Due to these participants experiencing train travel as a less attractive mode.

The bicycle path density is chosen as a characteristic with a similar approach as the total road density. This describes the robustness of the bicycle network. The values that are used are based on the bicycle path density for the province in which the region lies, obtained from CBS 2017. When this is relatively high, cyclists could have more direct routes to reach their destination and therefore have a shorter travel time. This makes cycling a more attractive mode of travel. This could mean that when this is relatively high, car users are more inclined to switch to cycling or cycle more often, due to a ‘better’ bicycle network. Adversely, when this is relatively low, car user might be less inclined to switch to cycling.

The thought behind choosing the number of delayed rides as a characteristic is that this represents the magnitude of the traffic related problems in that area. The values that are used are based on the number of delayed rides for the province in which the region lies, obtained from CBS 2017. A thought here is that when the number of delayed rides is relatively high, car user in that area have a higher sense of urgency to change their travel behavior. This due to their experience in delays in their area. Opposite to that, when the number of delayed rides would be relatively low, car users could not have a sense of urgency to change their travel behavior. They would not experience traffic related problems in their area and are therefore not triggered in changing their travel behavior.

Table 43 – Value of regional characteristics, linear regression outcomes

Source	Value	P-value
Intercept	16.36	0.17
Total road density	-2.745	0.18
Motorway density	-37.99	0.17
Railroad density	150.9	0.17
Bicycle path density	-25.15	0.18
Number of delayed rides	0.0001757	0.17
Number of movements, per density	0.0001294	0.19

What is most important to not from Table 43, is the signs belonging to the coefficients. When these are negative a negative correlation exists between the predictor and the performance of the dependent variable, in this case the activity of participants. This holds for motorway density, total road density and bicycle path density. Which means that when this increases, the activity of participants decreases. Adversely, for railroad density, delayed rides and number of movements when these increase the activity of participants increases as well. This is due to a positive correlation between the predictor and the activity of participants. The correlation of predictors could all be logically explained from a participant standpoint, except for bicycle path density. Here it would seem logical that when this is high, it would be more attractive to travel by bicycle than when this would be low. An alternative thought could be that when this is already high, the travelers who are willing to travel by bicycle already do and the ones that are left, whom are participating in the BPMs, are not that keen op travelling by bicycle either way. For both motorway density and total road density the negative correlation could be that when this is high, car users have multiple ways to travel by car and are therefore not avoiding peak, at least not by switching to an alternative mode, which a lot of BPMs are aimed at. For the railroad density to have a positive correlation and the bicycle path density a negative is kind of strange, due to them both being the supply side of an alternative mode of travelling. Both would therefore be presumed to be more attractive when this would be high. That the number of delayed rides and the number of movements per density has a positive correlation could be explained due to when this is high, the participants experience more hinder during their travel. They could therefore be inclined to be more active in avoiding peak.

What also is important to note is that the p-values for all variables were lower than 0.20, meaning that the values attached to these variables are accurate within a confidence interval of 80 percent.

The relation between the activity and the characteristics described here can be of use when roughly estimating the activity of participants of BPMs, when a similar BPM with a known activity, is performed in another region. For this estimation to work, the characteristics should be known for both regions.

The coefficients of a regression analysis could be used to draft a formula to predict the expected value for the BPMs. However, because all dependent variables are the same for all BPMs in that region, the expected value will always be the same as the average value for that region. This is therefore not used in this study.

9.4.4 Quantifying impact factors of BPMs

Table 44 - Quantifying the impact of TMP configuration and measure category on the activity of a BPM, linear regression outcomes

Source	Value	Standard error	t	Pr > |t|	Lower bound (95%)	Upper bound (95%)
Intercept	0.285	0.199	1.434	0.159	-0.116	0.685
Link to infrastructure	0.133	0.101	1.320	0.194	-0.070	0.337
Multiple mode options	0.311	0.108	2.877	0.006	0.093	0.528
Bicycle demand	-0.103	0.186	-0.554	0.582	-0.478	0.272
PT demand	-0.048	0.187	-0.257	0.799	-0.425	0.329
Multimodal demand	0.233	0.338	0.690	0.494	-0.448	0.914
General demand	-0.005	0.219	-0.023	0.982	-0.446	0.436
Employer	-0.054	0.228	-0.235	0.815	-0.514	0.406
Bicycle & PT demand	0.000	0.000				

Table 45 - Quantifying the impact of TMP configuration and region on the activity of a BPM, linear regression outcomes.

Source	Value	Standard error	t	Pr > |t|	Lower bound (95%)	Upper bound (95%)
Intercept	0.107	0.164	0.649	0.520	-0.225	0.439
Link to infrastructure	0.164	0.098	1.672	0.102	-0.034	0.361
Multiple mode options	0.232	0.134	1.735	0.090	-0.038	0.503
HGL	0.065	0.227	0.286	0.776	-0.392	0.522
LWD	0.193	0.216	0.893	0.377	-0.243	0.628
MAA	0.184	0.208	0.884	0.382	-0.237	0.605
MNL	0.085	0.176	0.481	0.633	-0.270	0.440
MRA	0.216	0.213	1.014	0.317	-0.214	0.646
NBR	0.148	0.206	0.719	0.476	-0.268	0.565
ZKN	0.000	0.000				

What can be seen from Table 44 and Table 45 is that despite reducing the number of variables, the components of measure type and region still are bad predictors. They all still have p-values above 0.30. The intercept however is a good predictor within an 80 percent confidence interval for the measure type.